Selected Fusion Applications: Defence and Civilian Domain

Wolfgang Koch
Dr. rer. nat. habil.

Fraunhofer FKIE, Wachtberg, GE

w.koch@ieee.org

1. **Aspects of Tracking-derived Anomaly Detection**
2. **Tracking of Extended Objects and Object Clusters**
3. **Fusion for Emerging Security and Civilian Topics**

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Anomaly Detection: Part of Situational Awareness

Fusing incomplete and imperfect pieces of complementary sensor and context information to focus human decision makers / decision making systems to events requiring special attention or actions.

Fusion-based anomaly detection is either unobtainable otherwise or exceeds what can be obtained by single sources in accuracy, reliability, or cost.

Here: emphasis on intuitively clear examples; no more general theory on “anomalous behavior”.

Key observation in tracking-driven anomaly detection:

The methods of target tracking and data fusion have actually evolved to a mature key technology, but their full potential of of enabling research and development in maritime situational awareness and anomaly detection still waits to be realized.

Promising approach to anomaly detection:

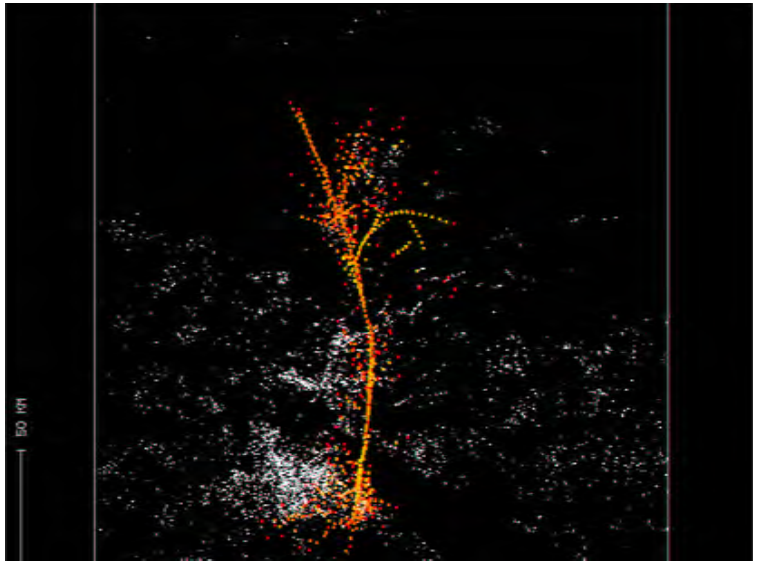
Tracking-derived Situation Elements

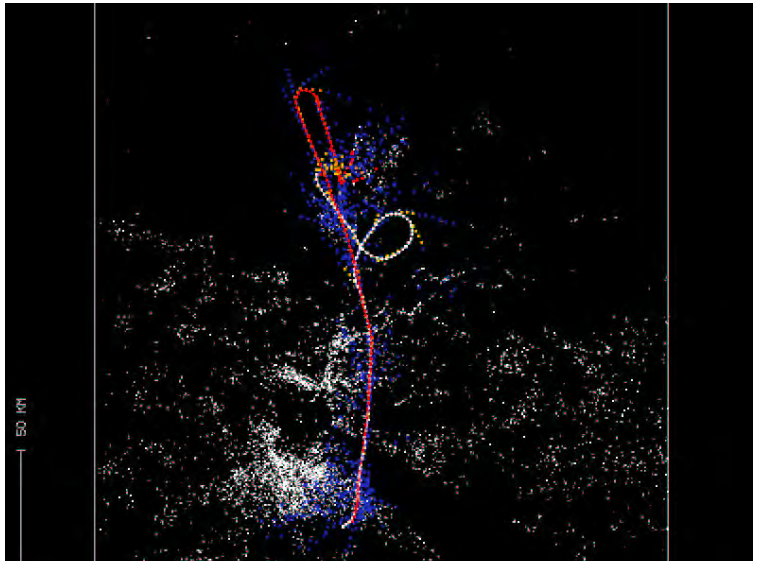
1. **Classification-based detection of anomalies**
2. **Violation of space-time regularity patterns**

Inferences Based on Retrodicted Tracks

Infer time invariant or slowly changing characteristics by exploiting gain in accuracy achievable by retrodiction.

- **Velocity history** (e.g. moving boats, vessels, helicopters, jet aircraft)
- **Acceleration history** (e.g. object type, “no more under-wing weapons”)
- **Heading, aspect angle** (e.g. threat evaluation, time-distributed spectra)
- **Rare events** (e.g. truck moving by night on a dirt road near a border)





Interceptor aircraft with clutter background making MHT / retrodiction methods inevitable.

Inferences based on Multitarget Tracks

Infer higher-JDL-level information related to mutual object interrelations from JDL-level-1 tracking results.

- **Object interrelations** (e.g. common history as an aircraft formation, convoy: impact on threat evaluation)
- **Target sources and sinks** (e.g. air fields, areas of concentration of military forces, classification by origin/designation)
- **Split-off events** (e.g. weapon launch: classification, bookkeeping: residual combat strength with impact on actions)
- **Stopping events** (e.g. missile launcher, target "waiting" for other objects: Establish interrelations.)
- **Collective motion** (e.g. convoys and marching columns: estimation of extension and target number.)

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Using *time invariant* or *slowly changing* knowledge about the overall behavior

Space-time regularity patterns: examples

- sea-/air-lanes as motion constraints
- planning information to be obeyed

Benefit of space-time regularity patterns

- improved the track accuracy/continuity
- pattern violation: ‘anomaly’ detection

Tracking-based motion pattern extraction

- generation of context knowledge
- fairly precise, timely information

On Integrating Planning Information into Tracking

- space-time waypoints $\mathcal{W}$ to be passed at given times via particular lanes
- tolerances: known error covariance matrices for each waypoint / object
- impact of waypoints if plan is kept: $p(\mathbf{x}_l|\mathcal{W}, \mathcal{Z}^k)$, “artificial sensor data”
- treat sensor data with time stamps before waypoints as “out-of sequence”
- if plan is kept: improved track accuracy / continuity, data association

Sequential Anomaly Detection: Pattern Violation

h_1: The observed objects obey an underlying pattern.
h_0: The pattern is not obeyed (e.g. off-lane, unplanned).

characterized by $P(\text{accept } h_1|h_1)$, $P(\text{accept } h_1|h_0)$.

Consider the ratio: $$\frac{p(h_1|Z^k)}{p(h_0|Z^k)} = \underbrace{\frac{p(Z^k|h_1)}{p(Z^k|h_0)}}_{=:\mathsf{LR}(k)} \frac{p(h_1)}{p(h_0)}.$$

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Calculate $\mathsf{LR}(k)$ iteratively using evolution / sensor models:

$$\mathsf{LR}(k) = \frac{\int d\mathbf{x}_k \, \overbrace{p(Z_k, m_k|\mathbf{x}_k)}^{\text{likelihood}} \, \overbrace{p(\mathbf{x}_k|Z^{k-1}, h_1)}^{\text{prediction}}}{\int d\mathbf{x}_k \, p(Z_k, m_k|\mathbf{x}_k) \, \underbrace{p(\mathbf{x}_k|Z^{k-1}, h_0)}_{\text{no pattern assumed}}} \mathsf{LR}(k-1).$$

Restart: re-confirm “normality” or to detect a violation at last.

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Aspects of Tracking-derived Anomaly Detection: First Papers

Schüller, G., Koch, W., Biermann, J., Behrend, A., Manthey, R., Pattern Recognition Using Queries in Relational Tracking Data Bases. *3rd Annual Skövde Workshop on Information Fusion Topics (SWIFT 2009), Skövde, Sweden, 12-14 Oct 2009*.

Koch, W., Biermann, J., Anomaly Detection from Tracking-derived Situation Elements. *NATO Workshop on Data Fusion and Anomaly Detection for Maritime Situational Awareness - MSA 2009, La Spezia, Italy, September 2009.*

NATO RTO IST-106 Research Task Group on

Information Filtering and Multi Source Information Fusion (RTG-051: RTGonMSIF)

Wolfgang Koch

Priv.-Doz. Dr. rer. nat., FIEEE

Head of Dept. Sensor Data

and Information Fusion

Fraunhofer FKIE, Germany

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Information Filtering and Multi Source Information Fusion

NATO NEC

situational awareness: timely, comprehensive, accurate
supply/retrieve information according to particular roles
exploit all available heterogeneous information sources

Existing Bottleneck

Real-time device-based information (obtained by sensor data fusion)
is poorly connected to
high level information fusion (mainly based on textual information).

Bridging the Gap

- **benefits for tactical and operational intelligence:**
  - ***threat detection and impact assessment***
- **benefits for related functions (military C2-ISR cycle):**
  - ***collection & mission planning, resource management***

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Lower-level Data + High-level Information from Civilian / Military Sources

Objective

Improve the entire intelligence process (object classification/identification, situation/impact assessment, process/refinement: JDL levels 1–5).

Novel Approach

Explore, demonstrate the potential of Battle Management Language (BML) as a unifying framework for the common representation of

- **domain aspects (available context)**
- **lower-level sensor data fusion results**
- **HUMINT, OSINT, soft data sources**

Particular Benefits

- **structured representation of situational elements gained by data fusion**
- **integration of context information (e.g. planning, geo-/environmental)**
- **transformation of soft data to computationally exploitable information**
- **definition of robust quality measures (various mathematical formalisms)**
- **threat models exploiting lower and higher levels of information fusion**

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Links to Reality

- Scenarios from the MAJIIC-context (connection to C2-IRS)
- Looking at / quantifying of improvements for:
  video stream analysis, passive radar data exploitation, emitter localization, anomalous behavior detection, fusion of sensor & HUMINT/OSINT reports, …
- Recommendations of enhancement of coalition BML
- Dissemination of results, e.g. by special sessions at
  annual International Conference on Information Fusion (ISIF IEEE FUSION)
  NATO RSY 183 "Persistent Surveillance - Networks, Sensors and Architecture"

Participating Nations	DEU, EST, FRA, POL, PRT, ESP, SWE, TUR, USA
Start-End	2011 - 2013
Meetings	ET: March 22-24, 2011, Fraunhofer FKIE, DEU
	Kick-off: June 27 – 29, 2011, RTA, Paris, FRA
Organizer	Wolfgang Koch, Fraunhofer FKIE, DEU

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3. Looking at Emerging Security and Civilian Topics

Ausgedehnte Zielobjekte

- Ein Objekt, mehrere variierende Streuzentren

Gruppen / Formationen

- Mehrere dicht operierende Ziele, möglicherweise unaufgelöst

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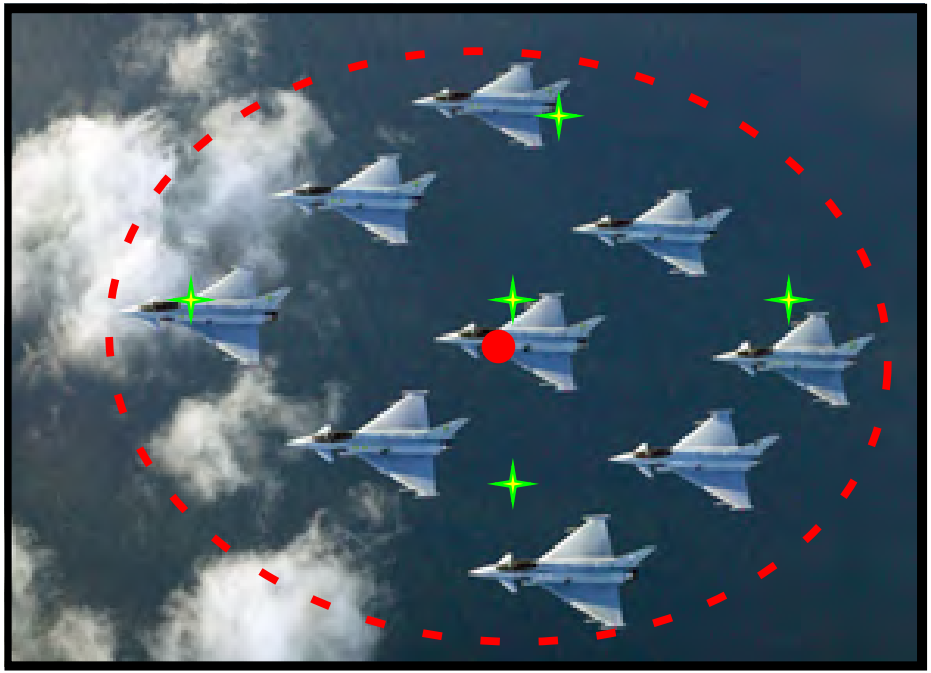
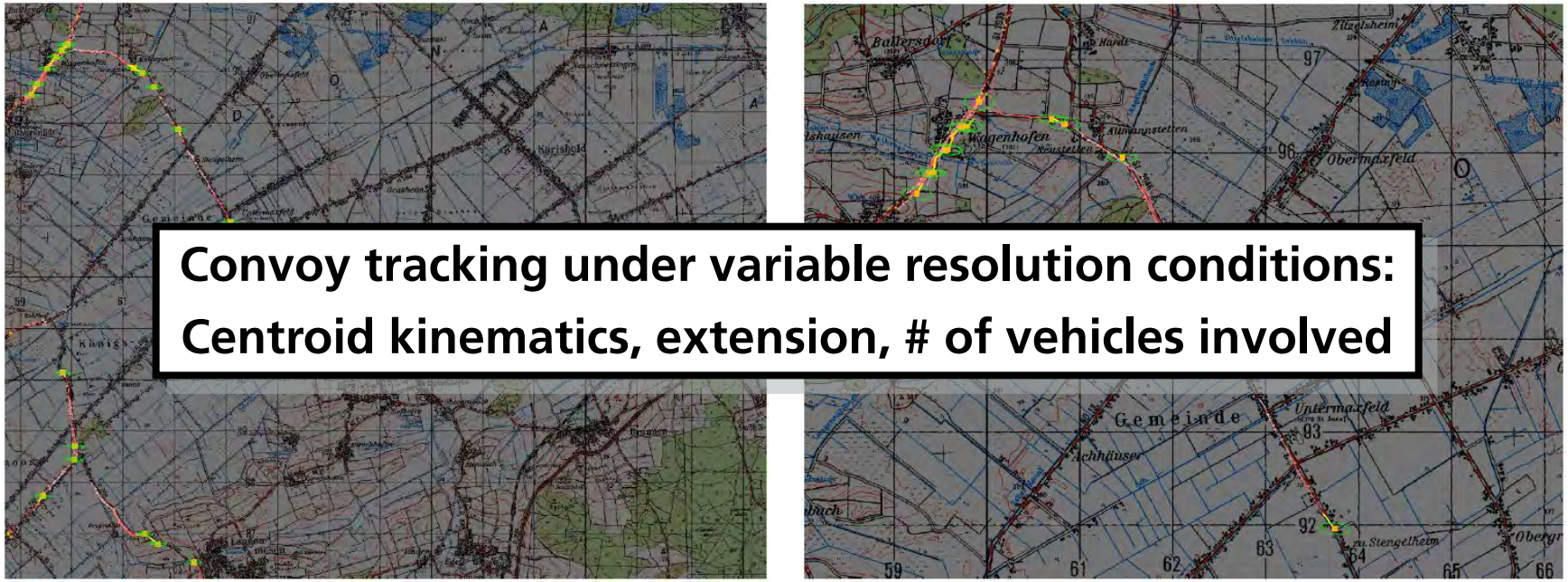
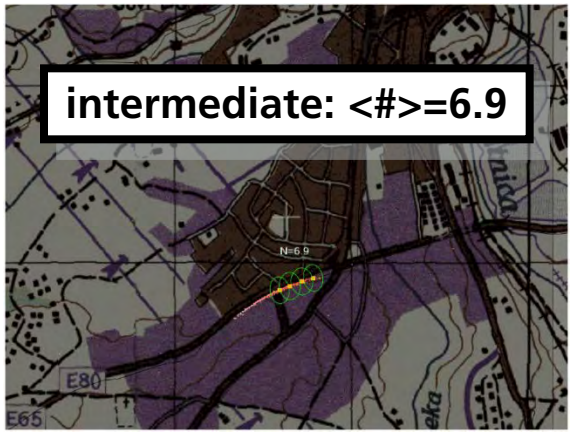


Multiple Target Tracking:MAJIIC-Expamles





object extension: ‘covariance-type’ matrices

- state augmentation by a random matrix
  - object extension exceeding resolution
  - closely spaced vehicle convoys
  - collectively moving object clouds

integration of available context information

- GMTI radar: Doppler blindness (MDV)
- digital road-map information (GIS)

Elements for Situation Pictures: Tracks of Time-varying Objects

Which object properties are of interest? $\rightarrow$ ***state*** X_k ***at time*** t_k

- road-moving vehicle: odometer count x_k $\quad X_k = (x_k, \dot{x}_k)$
- position, speed, acceleration: $\quad X_k = (\mathbf{r}_k, \dot{\mathbf{r}}_k, \ddot{\mathbf{r}}_k)$
- joint state of several objects: $\quad X_k = (\mathbf{x}_k^1, \mathbf{x}_k^2, \ldots)$
- attributes, e.g. radar cross section $x_k \in \mathbb{R}^+$: $X_k = (\mathbf{x}_k, x_k)$
- maneuvering phase, object class $i_k \in \mathbb{N}$: $\quad X_k = (\mathbf{x}_k, i_k)$
- object shape: SPD random matrices $\mathbf{X}_k$ $\quad X_k = (\mathbf{x}_k, \mathbf{X}_k)$

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Generalize BAYESian tracking to extended objects.

n_k plots $Z_k = \{\mathbf{z}_k^j\}_{j=1}^{n_k}$ at time t_k, accumulated data $\mathcal{Z}^k = \{Z_k, n_k, \mathcal{Z}^{k-1}\}$

The conditional pdf $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$ describes what is known about the extended object state $\mathbf{x}_k, \mathbf{X}_k$ based on all sensor data up to time t_k.

'extended object tracking': *iterative* calculation of $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$.

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- $p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k) = p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^k)\, p(\mathbf{X}_k|\mathcal{Z}^k)$ **extended object 'track'**
- $p(Z_k, n_k|\mathbf{x}_k, \mathbf{X}_k)$ **sensor output to be processed, i.e. the likelihood**
- $p(\mathbf{x}_k|\mathcal{Z}^k) = \int d\mathbf{X}_k\, p(\mathbf{x}_k, \mathbf{X}_k|\mathcal{Z}^k)$ **kinematics of the extended object**

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  $p(\mathbf{x}_k|\mathbf{X}_k, \mathcal{Z}^k)$: **assume Gaussian density**

  $p(\mathbf{X}_k|\mathcal{Z}^k)$: **assume inverse Wishart density**

Sensor Output: Structure of the Likelihood Function

in general: $p(Z_k, n_k | \mathbf{x}_k, \mathbf{X}_k, Z^{k-1}) = p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k)\, p(n_k | \mathbf{x}_k, \mathbf{X}_k)$

(assumed for the moment: no false measurements, well-separated objects)

'de facto' measured: cbject centroid $\mathbf{H}_k \mathbf{x}_k$

shape to be estimated: 'measurement error' $\mathbf{X}_k$

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$$p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k) = \prod_{j=1}^{n_k} \mathcal{N}\Big(\mathbf{z}_k^j;\, \mathbf{H}_k \mathbf{x}_k,\, \mathbf{X}_k\Big) \quad \text{(indep. data)}$$

$$\propto \underbrace{\mathcal{N}\Big(\mathbf{z}_k;\, \mathbf{H}_k \mathbf{x}_k,\, \tfrac{1}{n_k}\mathbf{X}_k\Big)}_{\textbf{Gauß density}} \underbrace{\mathcal{LW}\Big(\mathbf{Z}_k;\, n_k - 1,\, \mathbf{X}_k\Big)}_{\textbf{Wishart density}}$$

$$\mathbf{z}_k = \frac{1}{n_k} \sum_{j=1}^{n_k} \mathbf{z}_k^j, \quad \mathbf{Z}_k = \sum_{j=1}^{n_k} (\mathbf{z}_k^j - \mathbf{z}_k)(\mathbf{z}_k^j - \mathbf{z}_k)^\top, \quad \textbf{'scattering matrix'}$$

$$\mathcal{LW}\big(\mathbf{Z}_k;\, n_k - 1,\, \mathbf{X}_k\big) = |\mathbf{X}_k|^{-\frac{n_k - 1}{2}} \operatorname{etr}\big[-\tfrac{1}{2}\mathbf{Z}_k \mathbf{X}_k^{-1}\big]$$

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Structure of the Density $p(\mathbf{x}_k, \mathbf{X}_k | Z^k)$ after Filtering

$$p(\mathbf{x}_k, \mathbf{X}_k | Z^k) \propto p(Z_k | n_k, \mathbf{x}_k, \mathbf{X}_k)\, p(\mathbf{x}_k, \mathbf{X}_k | Z^{k-1}) \propto \underbrace{\mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k} \otimes \mathbf{X}_k\big)}_{\text{KALMAN update}}$$

$$\times \underbrace{|\mathbf{X}_k|^{-\frac{1}{2}}\, \mathrm{etr}\big[-\tfrac{1}{2}\mathbf{N}_{k|k-1}\mathbf{X}_k^{-1}\big]}_{\text{innovation factor}}\, \underbrace{\mathcal{LW}\big(\mathbf{Z}_k;\, n_k - 1,\, \mathbf{X}_k\big)}_{\text{from likelihood fct.}}\, \underbrace{\mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k-1},\, \mathbf{X}_{k|k-1}\big)}_{\text{inverse Wishart density!}}$$

up to constant factors with innovation covariance $S_{k|k-1}$ and innovation matrix $\mathbf{N}_{k|k-1}$:

$$\mathbf{N}_{k|k-1} = S_{k|k-1}^{-1}\big(\mathbf{z}_k - \mathbf{H}_k\mathbf{x}_{k|k-1}\big)\big(\mathbf{z}_k - \mathbf{H}_k\mathbf{x}_{k|k-1}\big)^\top$$

Structure of the Density $p(\mathbf{x}_k, \mathbf{X}_k | Z^k)$ after Filtering

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generalized Kalman filter: $p(\mathbf{x}_k, \mathbf{X}_k | Z^k) \propto \underbrace{\mathcal{N}\big(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k} \otimes \mathbf{X}_k\big)}_{\text{KALMAN update}}\, \underbrace{\mathcal{IW}\big(\mathbf{X}_k;\, \nu_{k|k},\, \mathbf{X}_{k|k}\big)}_{\text{extension update}}$

with simple update equations: $\mathbf{X}_{k|k} = \mathbf{X}_{k|k-1} + \mathbf{N}_{k|k-1} + \mathbf{Z}_k, \quad \nu_{k|k} = \nu_{k|k-1} + n_k.$

innovation matrix $\mathbf{N}_{k|k-1}$: point source object tracking with *unknown* measurement error cov. or tracking *completely unresoved* object groups.

marginalization of the joint density $p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k)$

sometimes: interest in estimates of the kinematical state $\mathbf{x}_k$ only

$$
\begin{aligned}
p(\mathbf{x}_k | \mathcal{Z}_k) &= \int d\mathbf{X}_k \, p(\mathbf{x}_k, \mathbf{X}_k | \mathcal{Z}^k) \\
&= \int d\mathbf{X}_k \, \mathcal{N}\Big(\mathbf{x}_k;\, \mathbf{x}_{k|k},\, \mathbf{P}_{k|k} \otimes \mathbf{X}_k\Big) \, \mathcal{IW}\Big(\mathbf{X}_k;\, \nu_{k|k},\, \mathbf{X}_{k|k}\Big)
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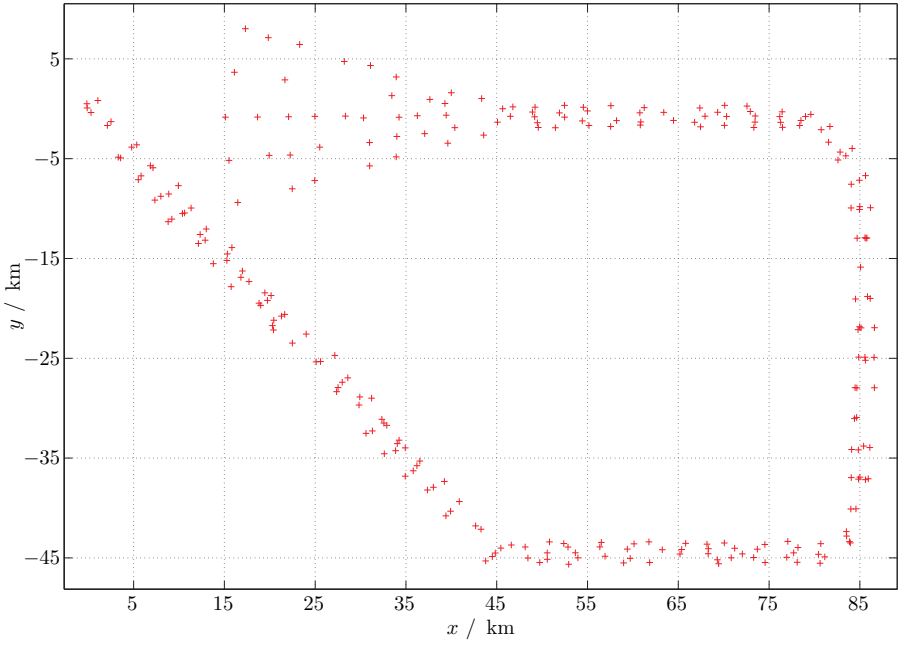
&= \mathcal{T}\Big(\mathbf{x}_k;\, \nu_{k|k} + s(1-d),\, \mathbf{x}_{k|k}, \mathbf{P}_{k|k} \otimes \mathbf{X}_{k|k}\Big) \quad \textbf{(standard algebra!)}
\end{aligned}
$$

multivariate Student-t-density with $\nu_{k|k}$ degrees of freedom

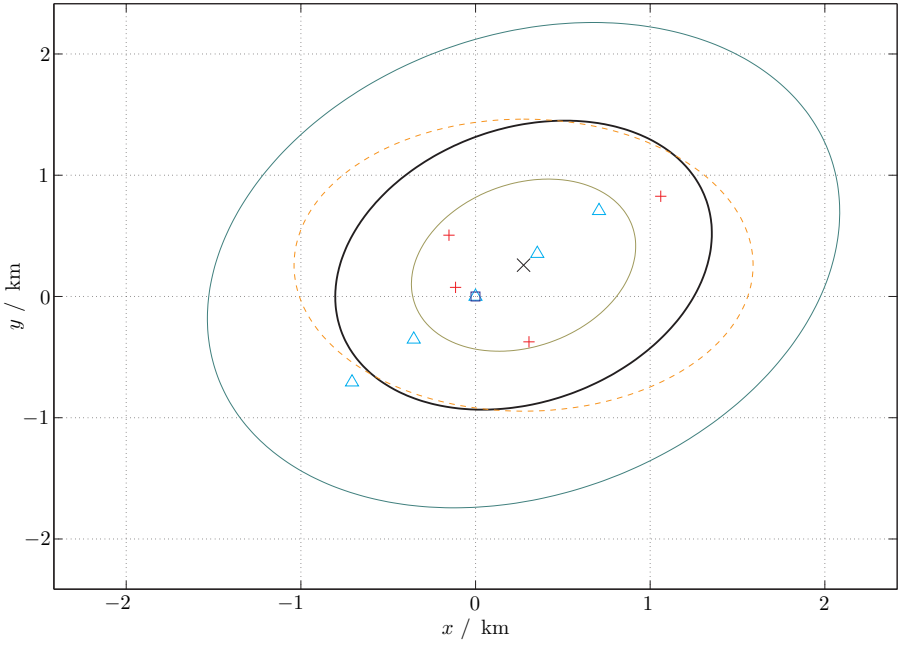
basis for kinematical state estimates with related error covariance matrices,

calculation of expectation gates, extended object track-to-track correlation/fusion, . . .

Messungen



Trackingergebnisse



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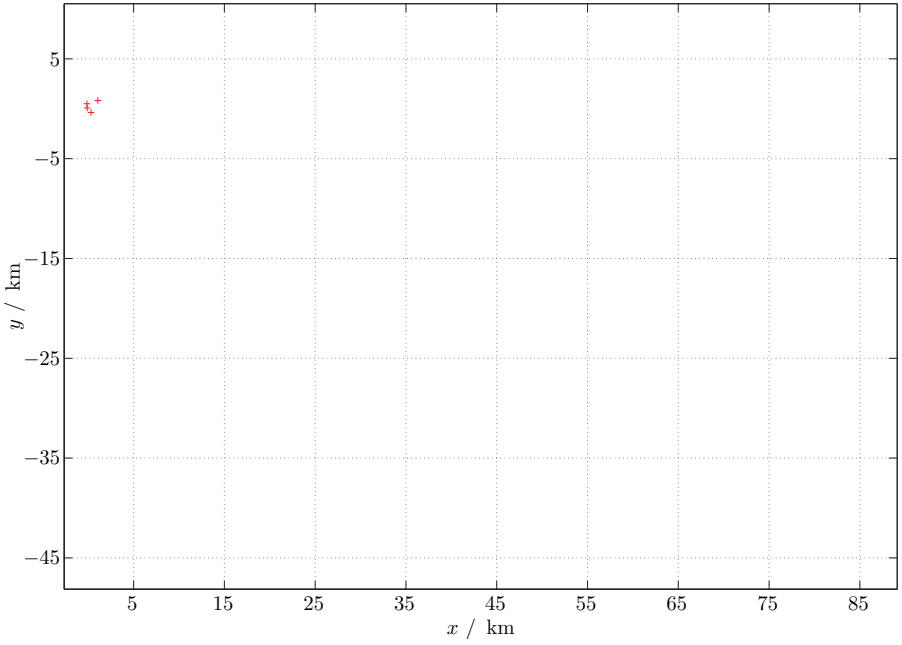

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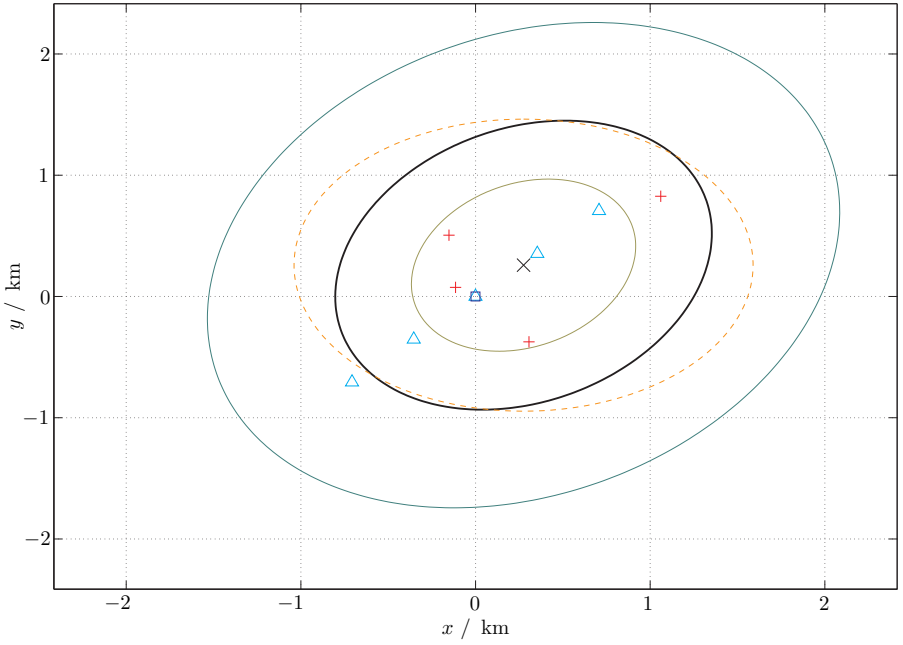

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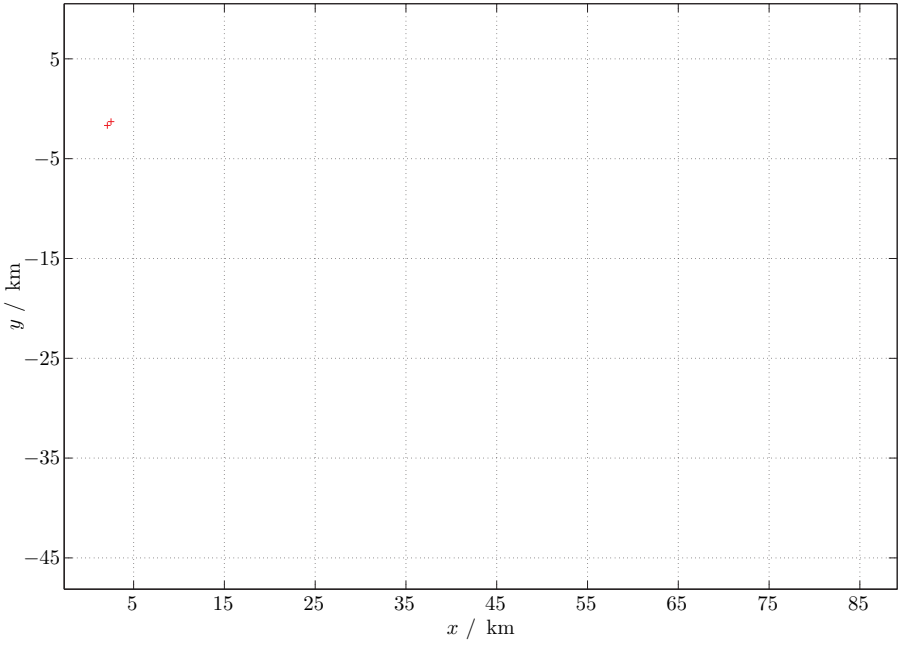

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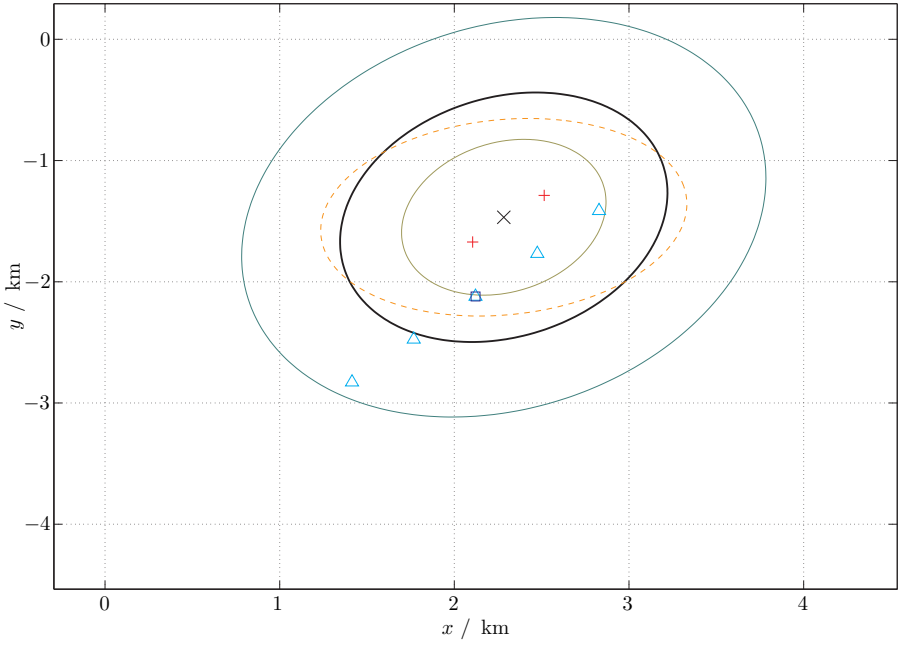

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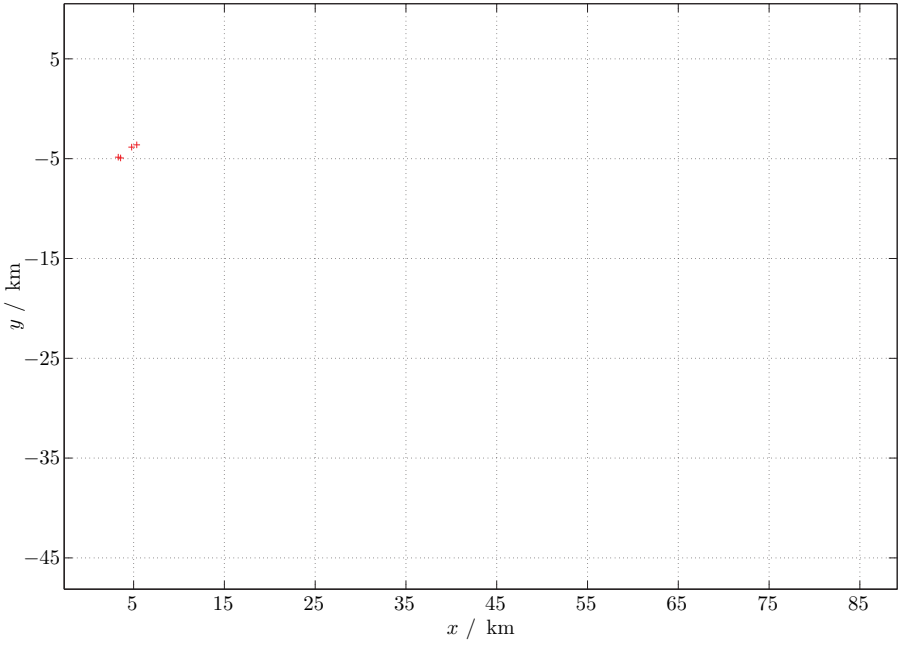

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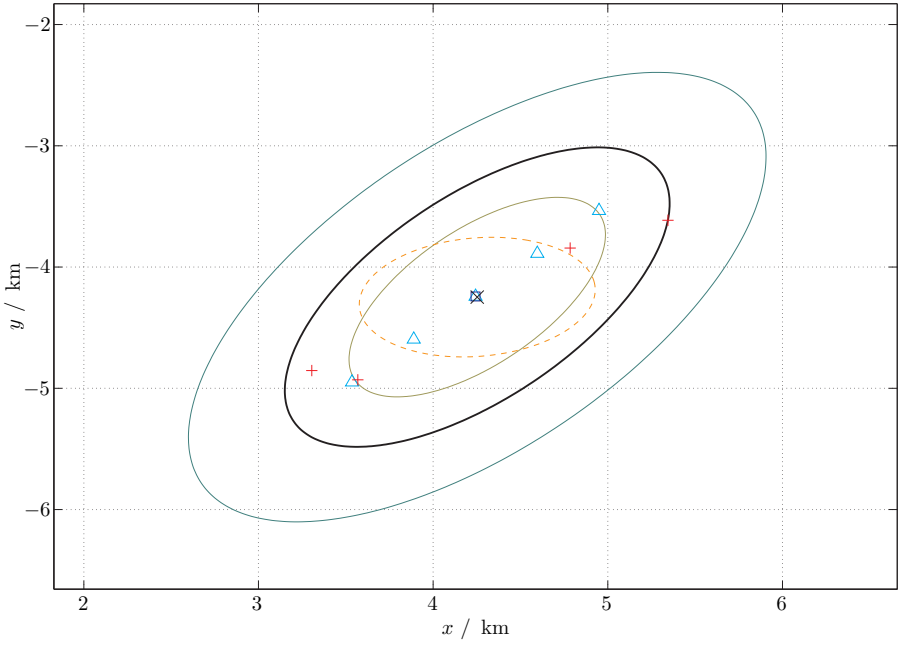
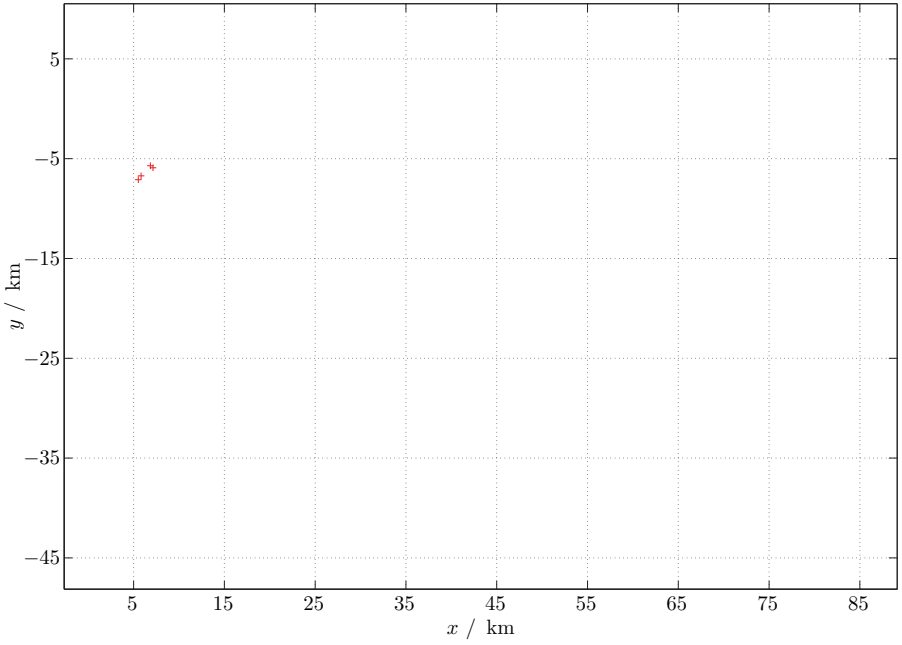


Messungen



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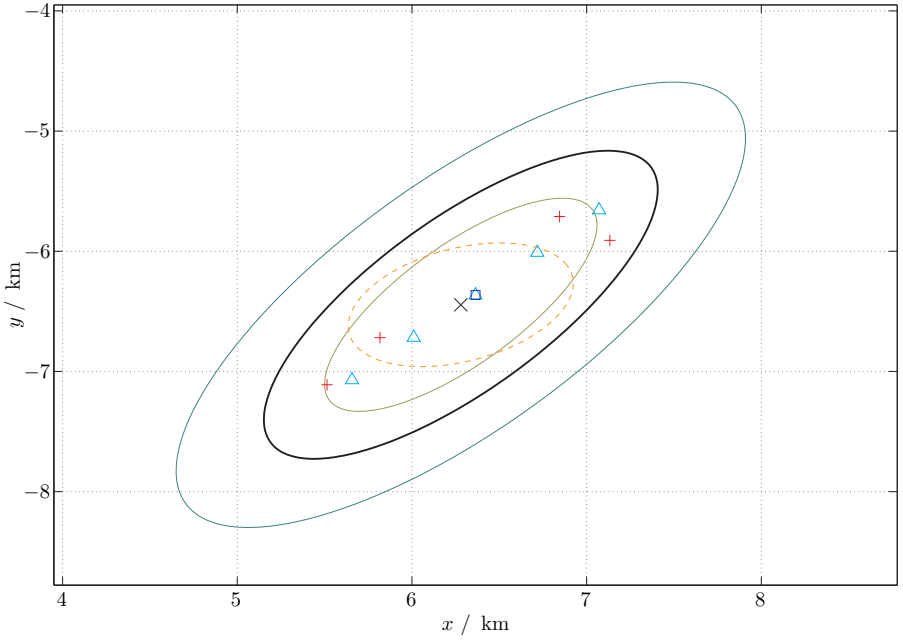

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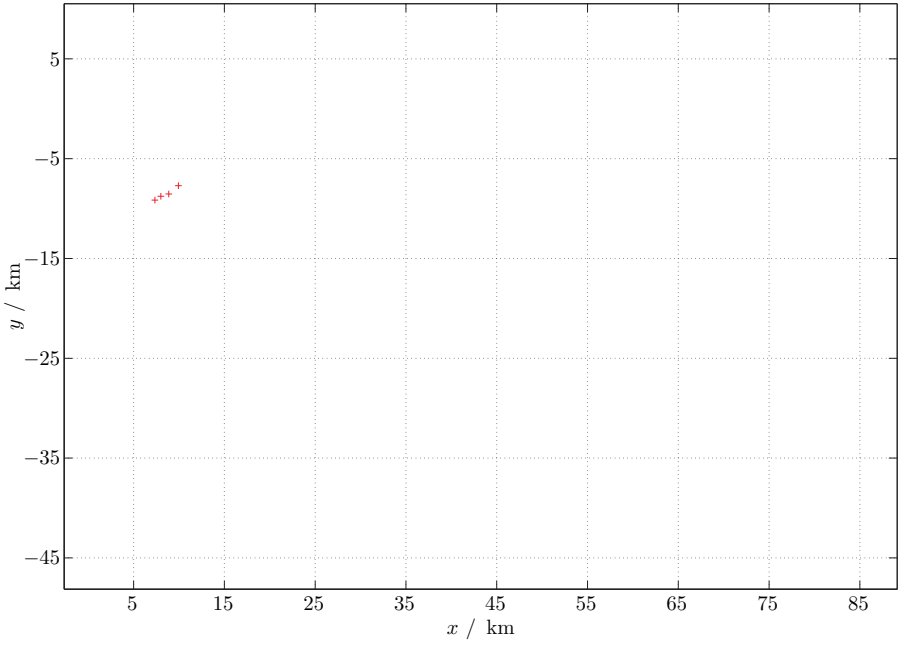

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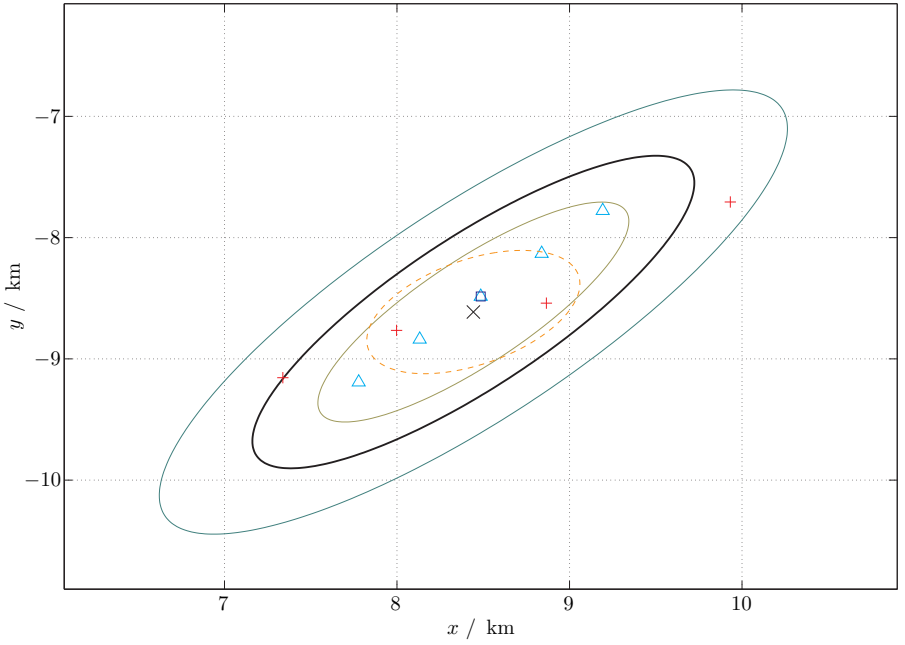

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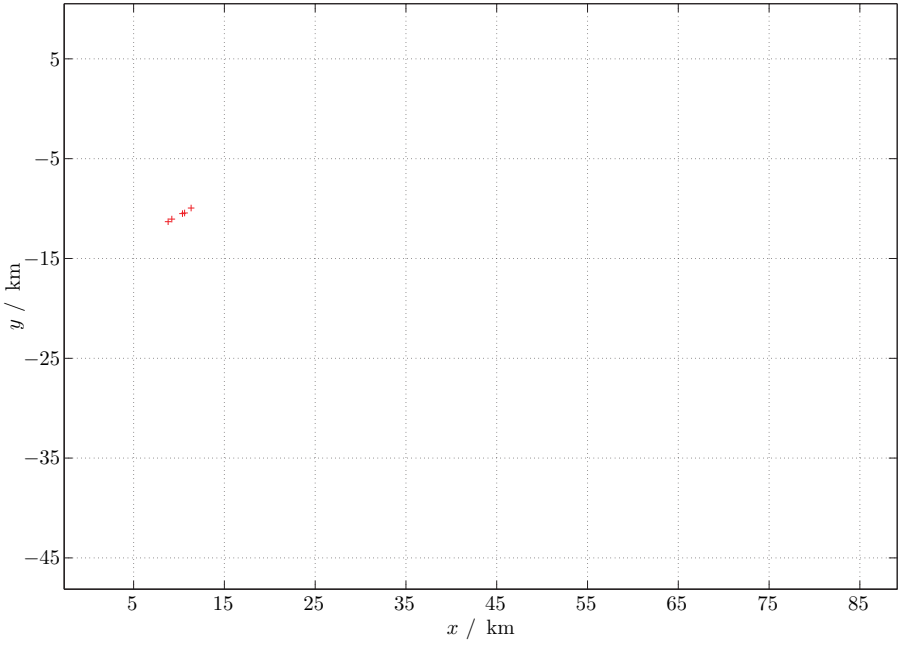

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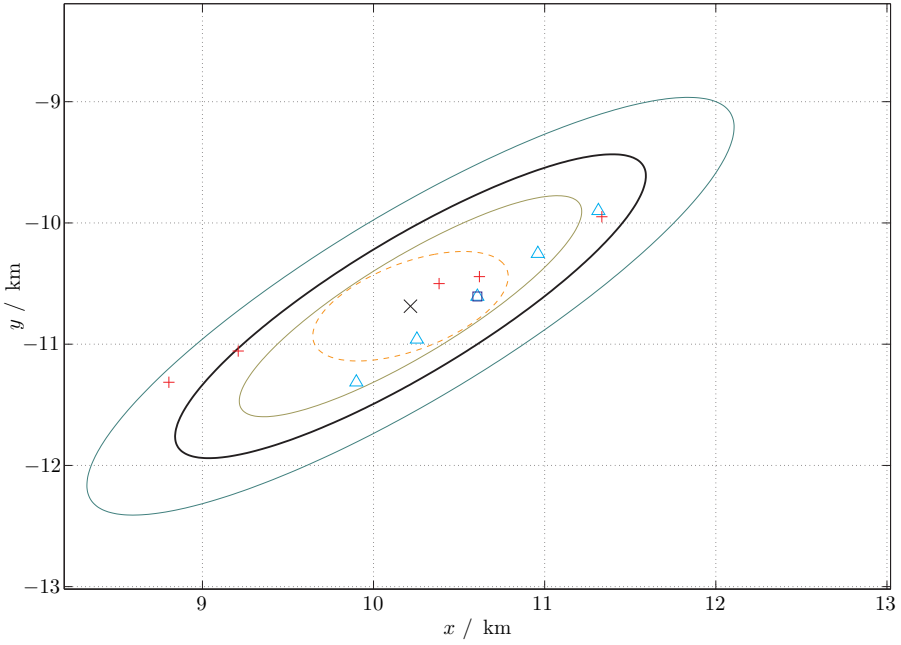

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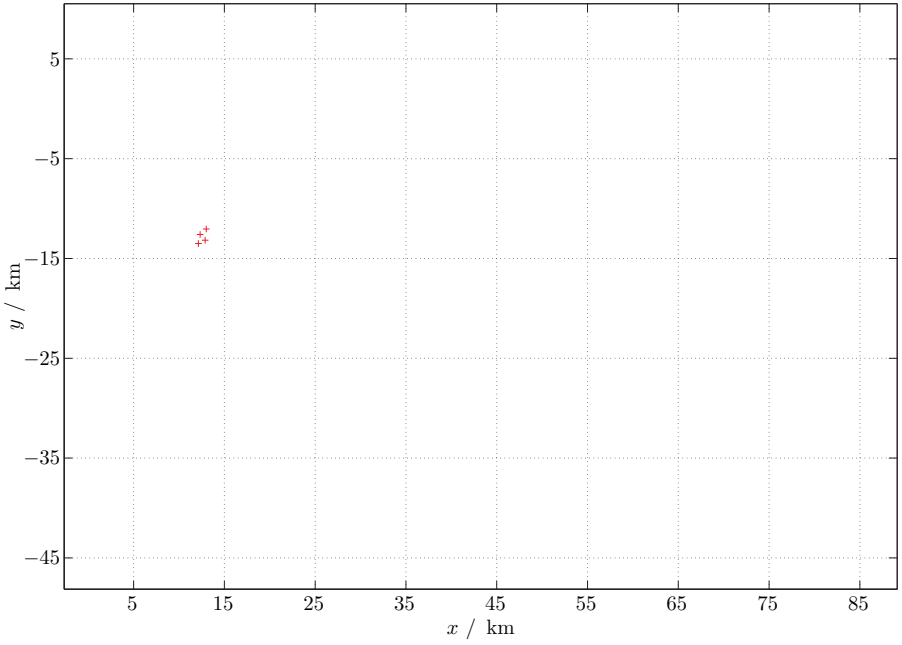

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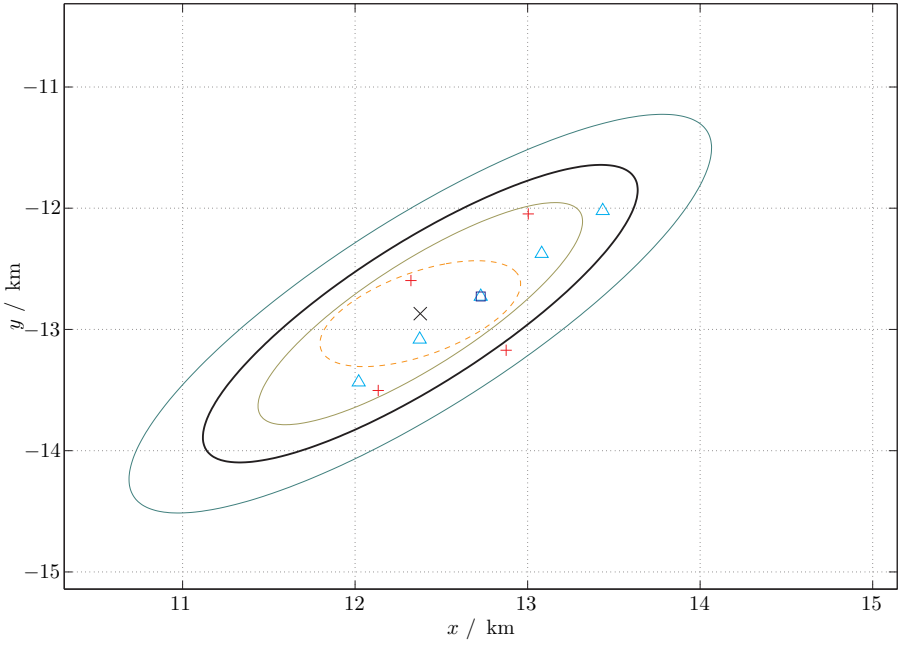

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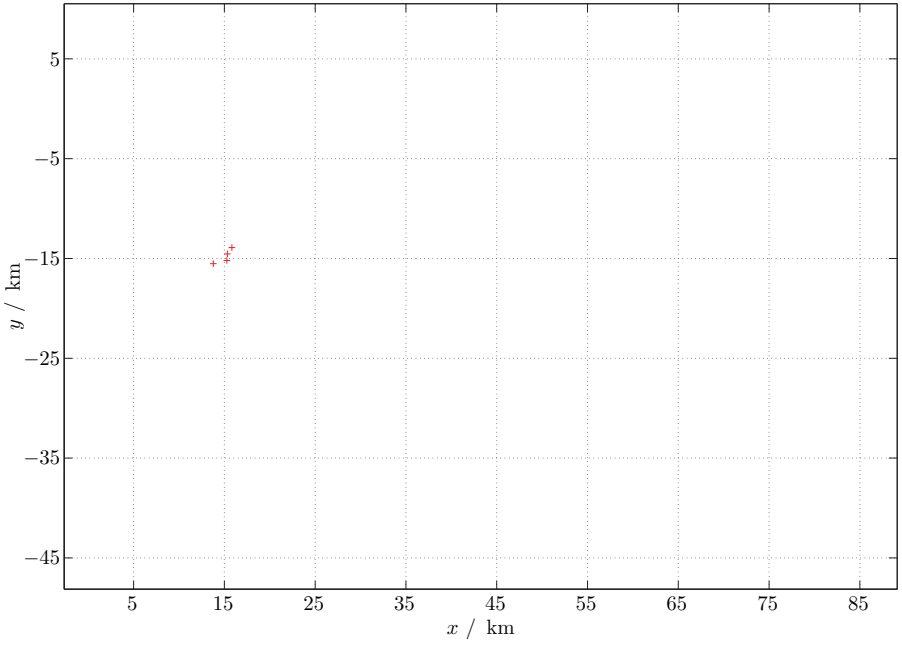

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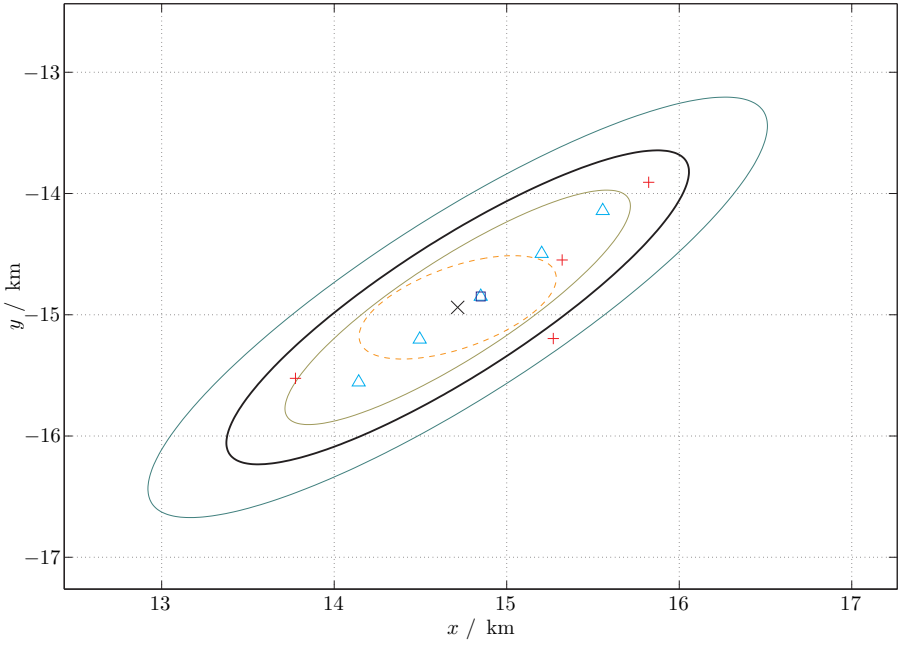

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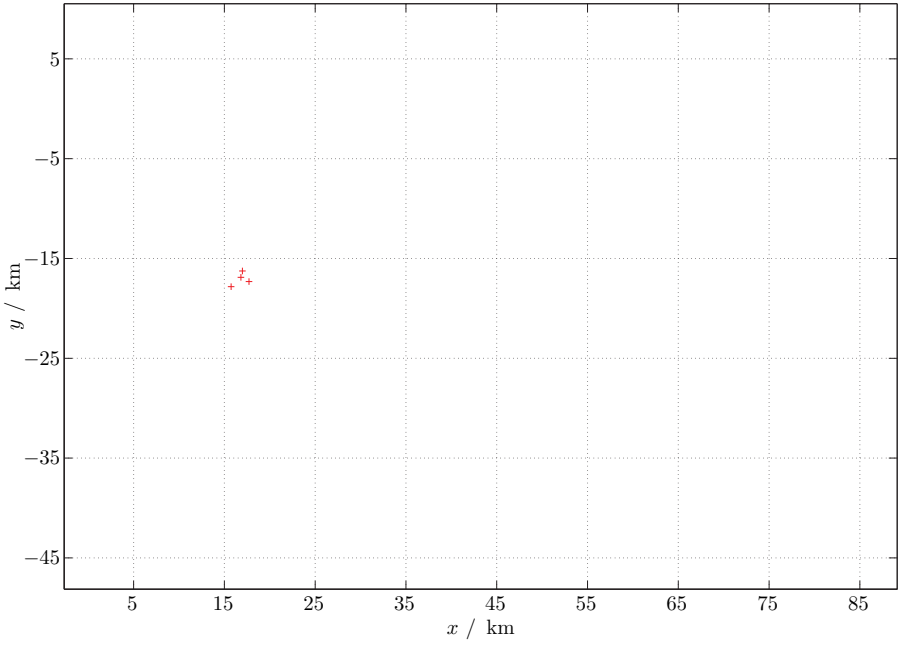

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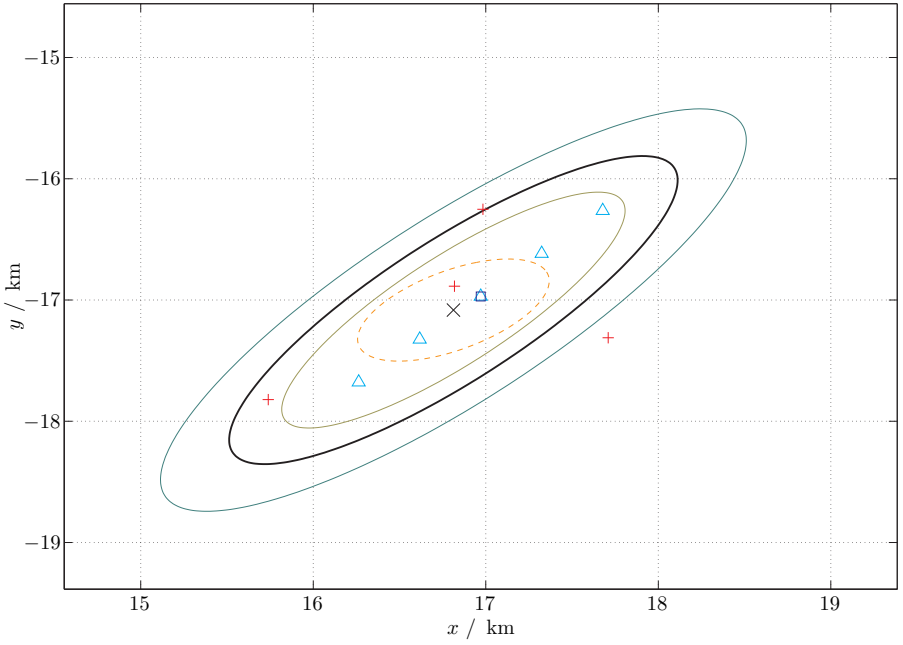

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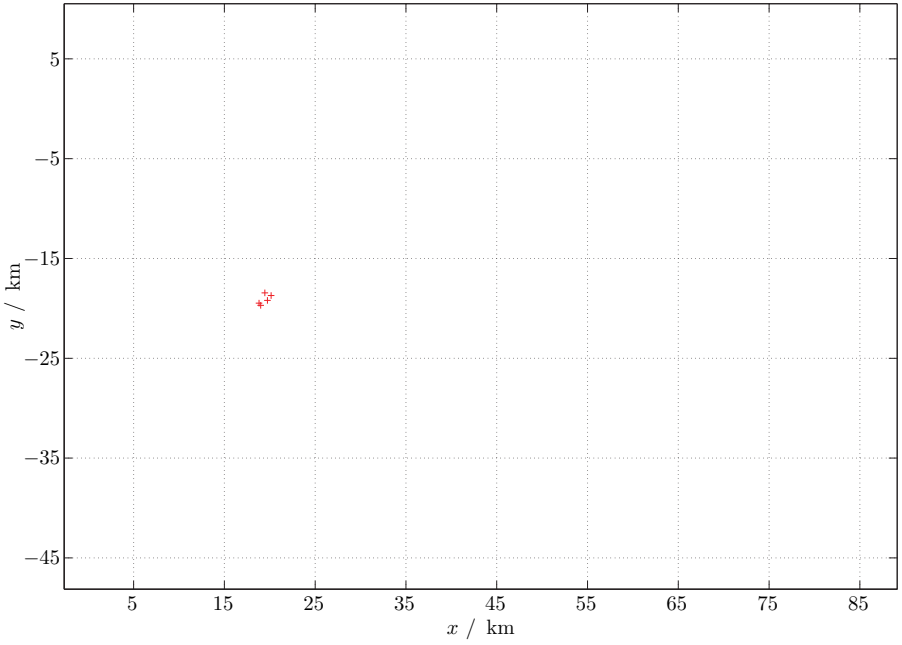

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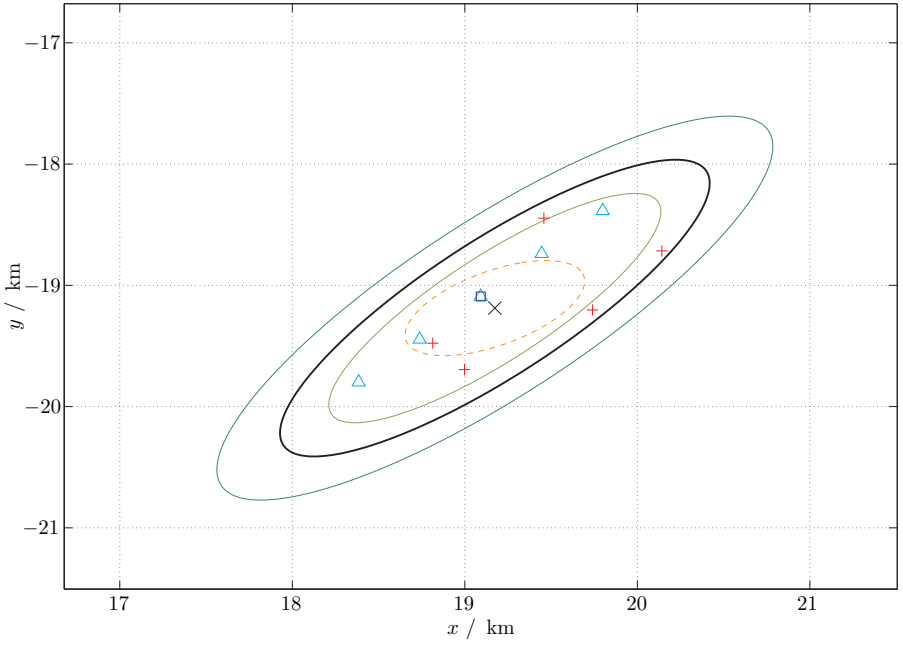

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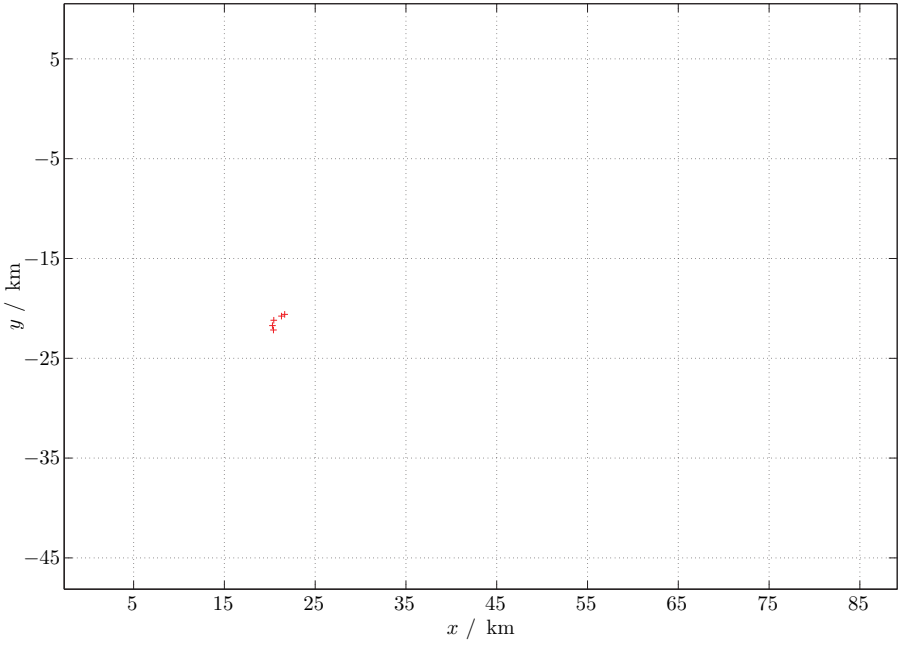

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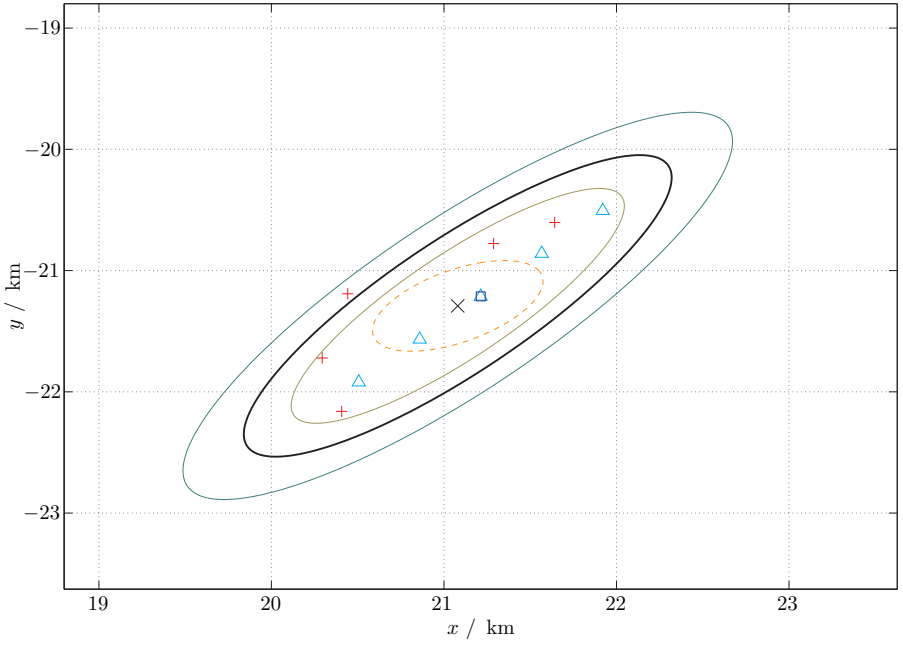

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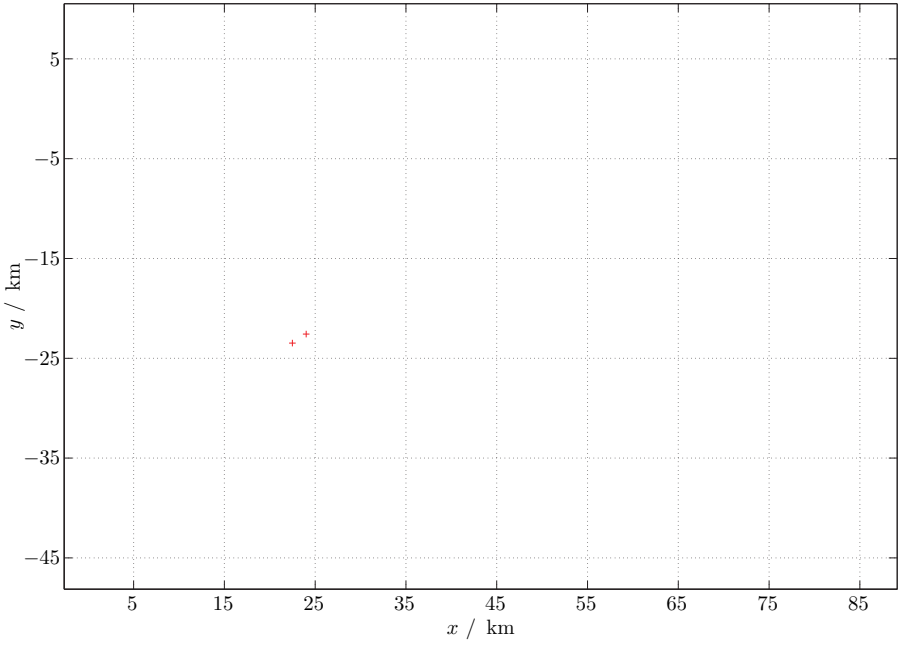

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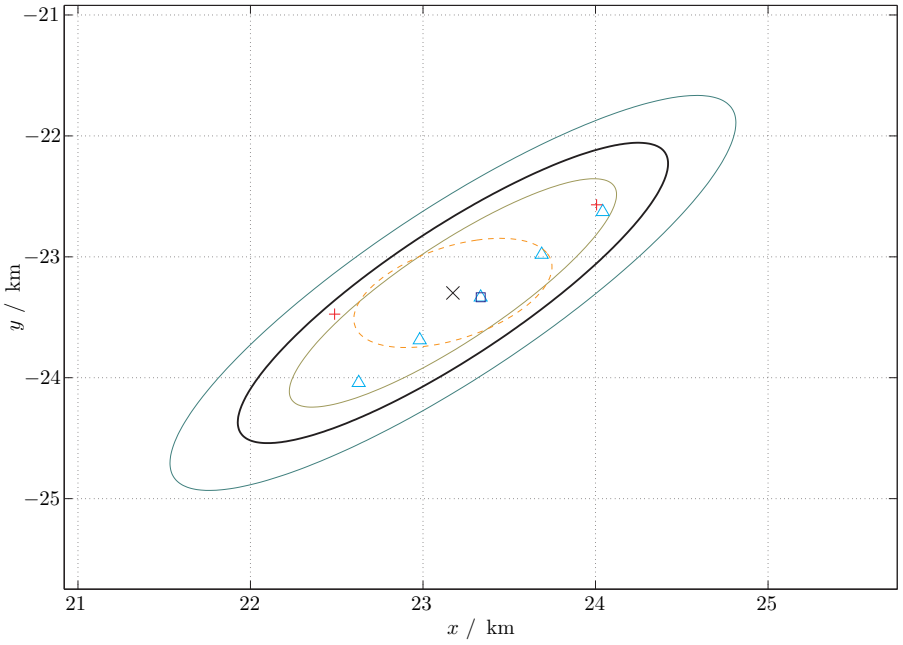

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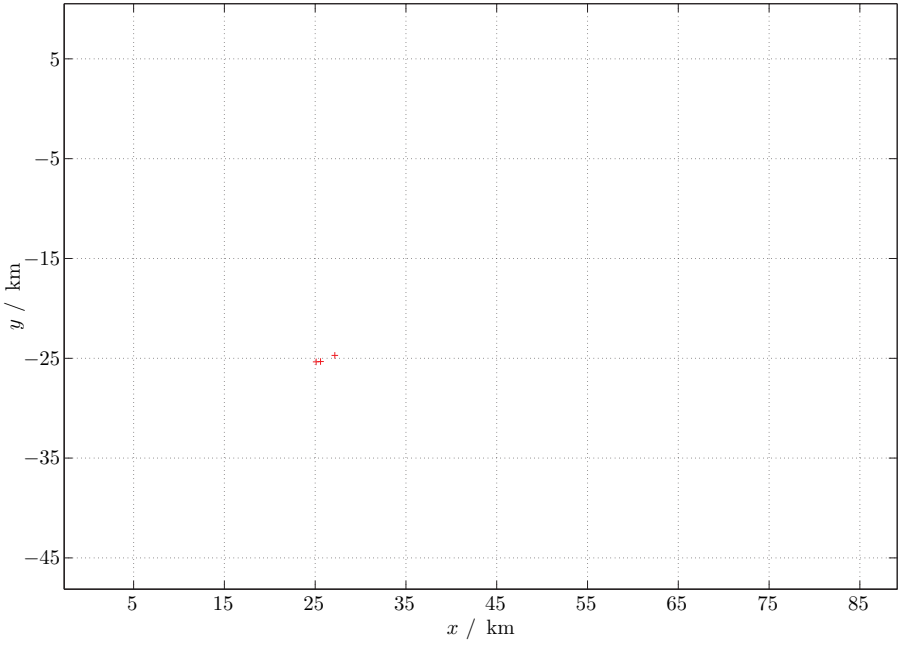

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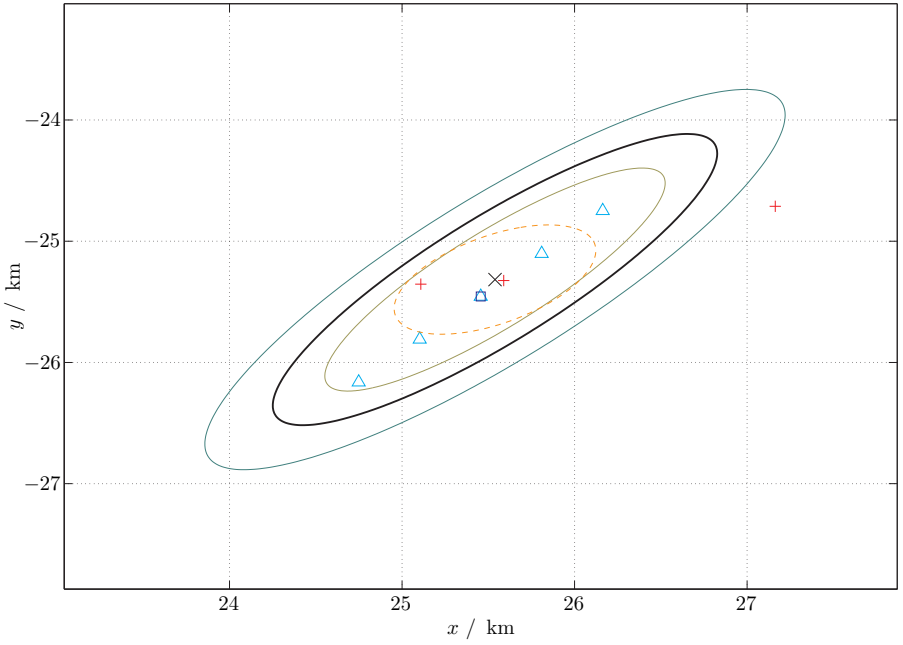

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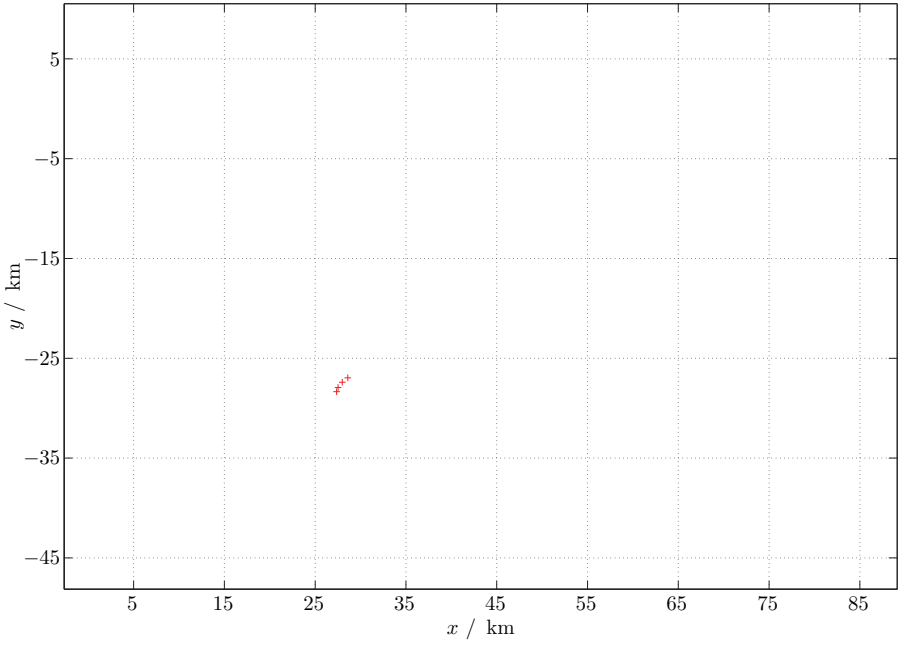

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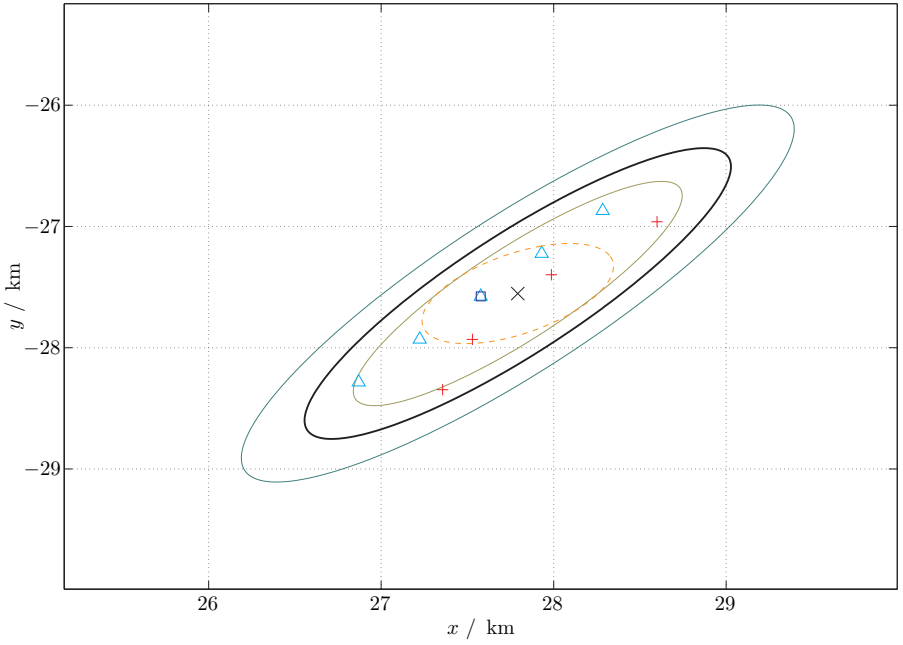

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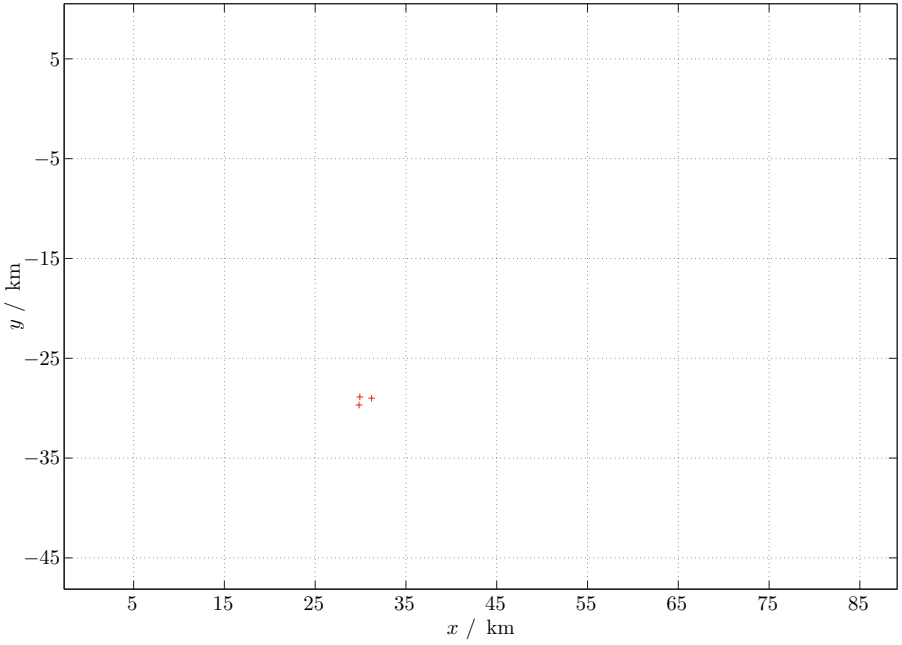

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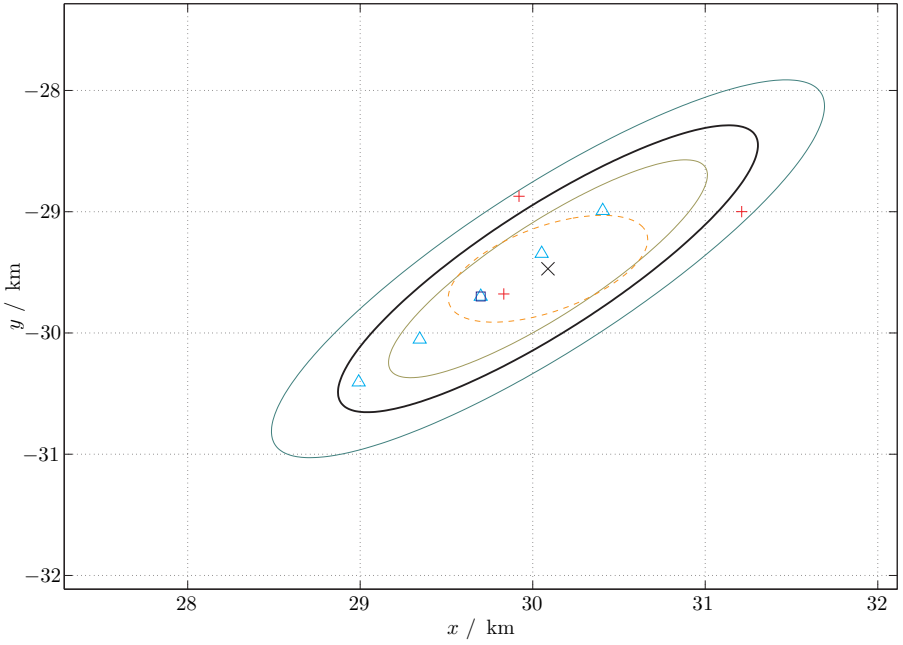

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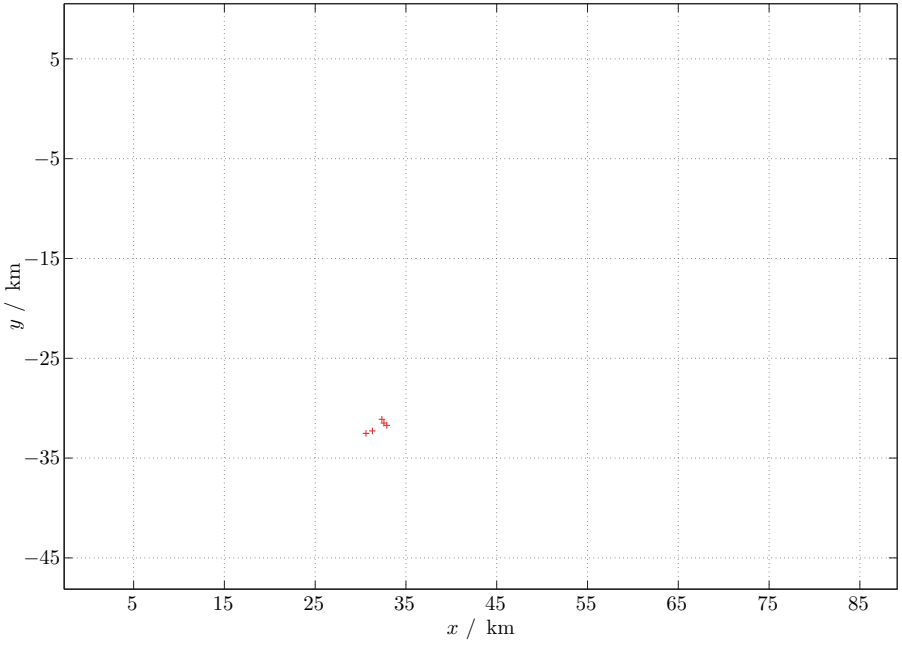

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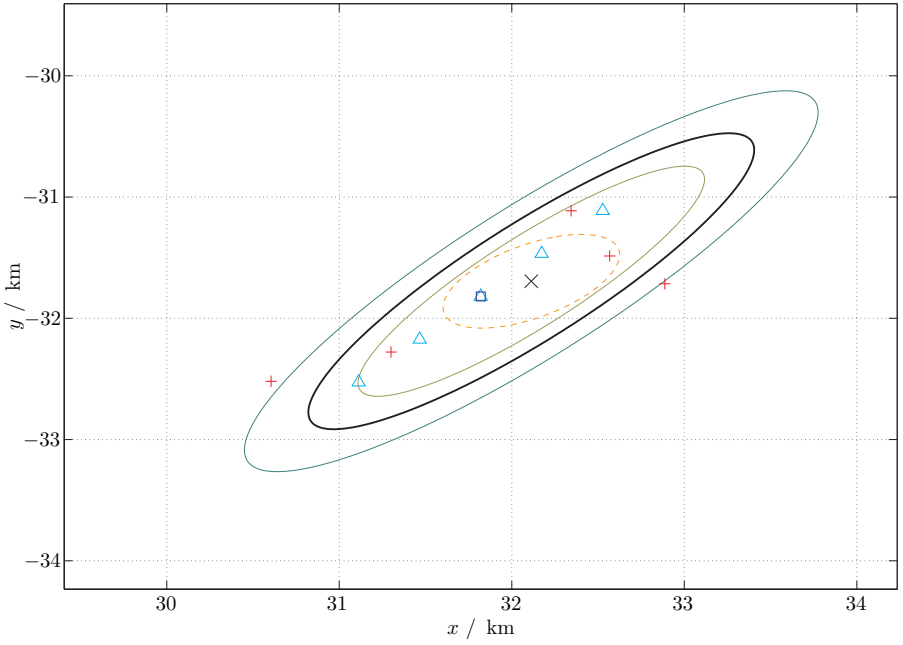

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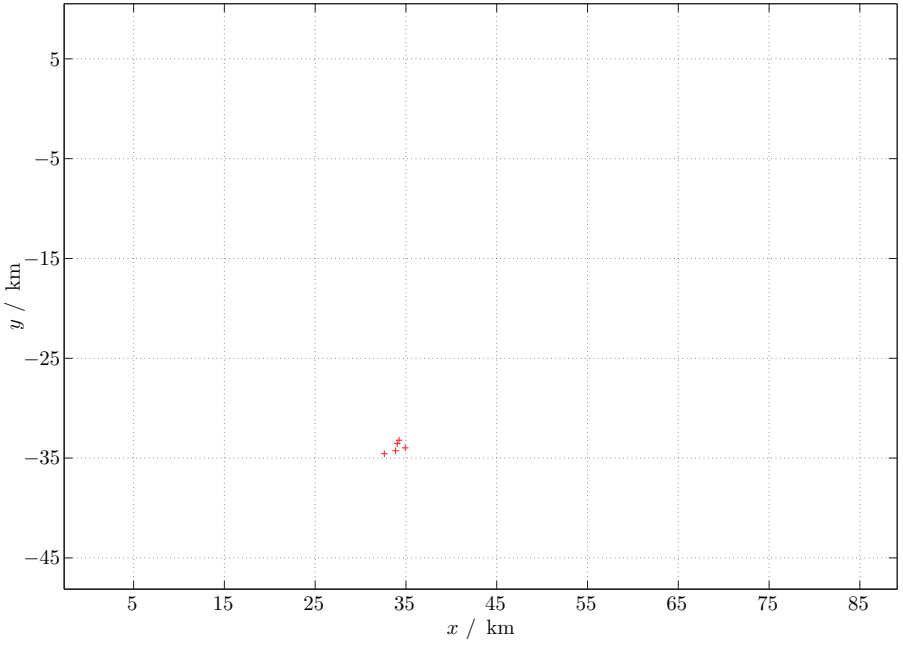

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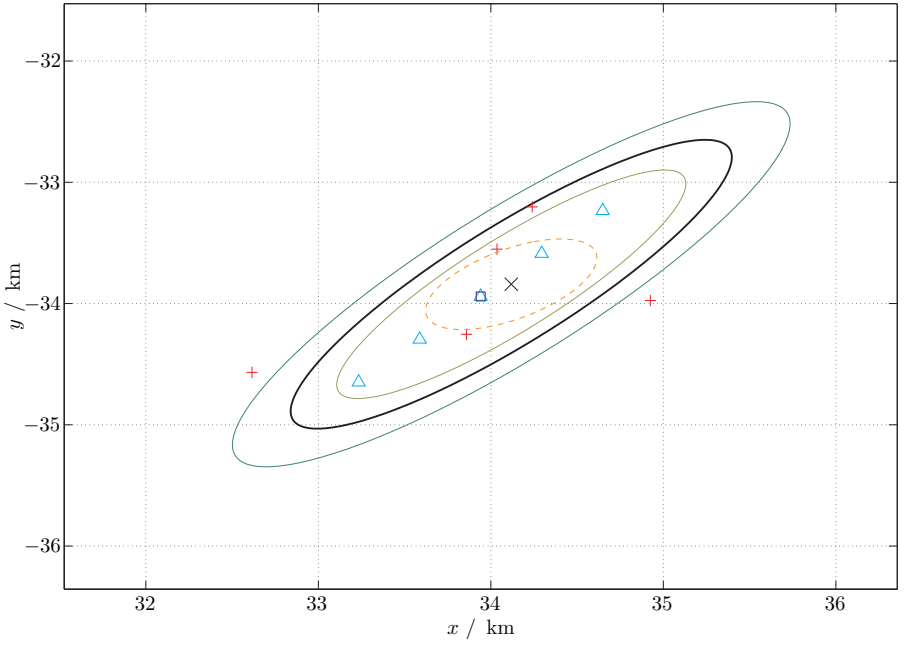

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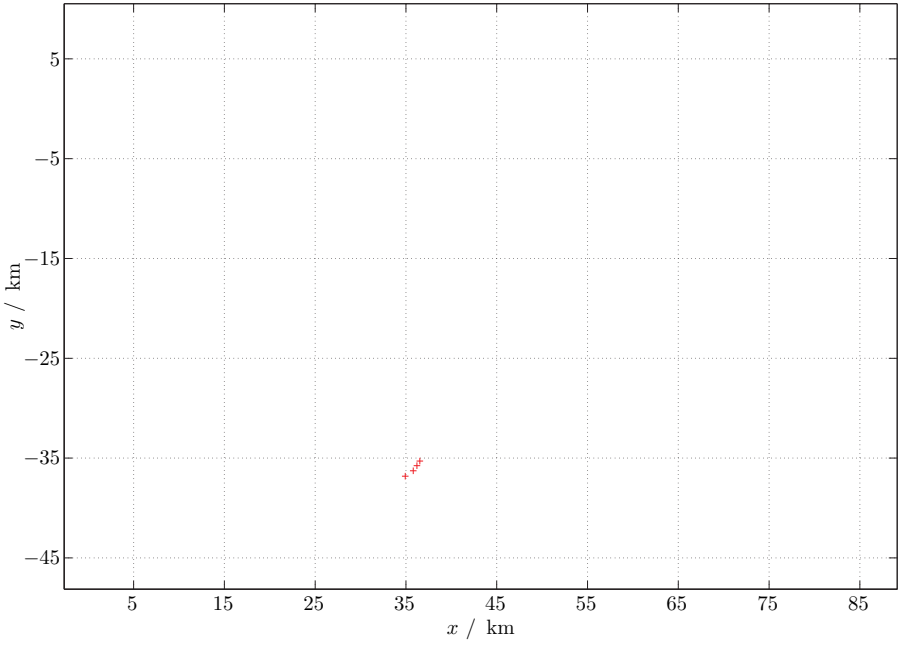

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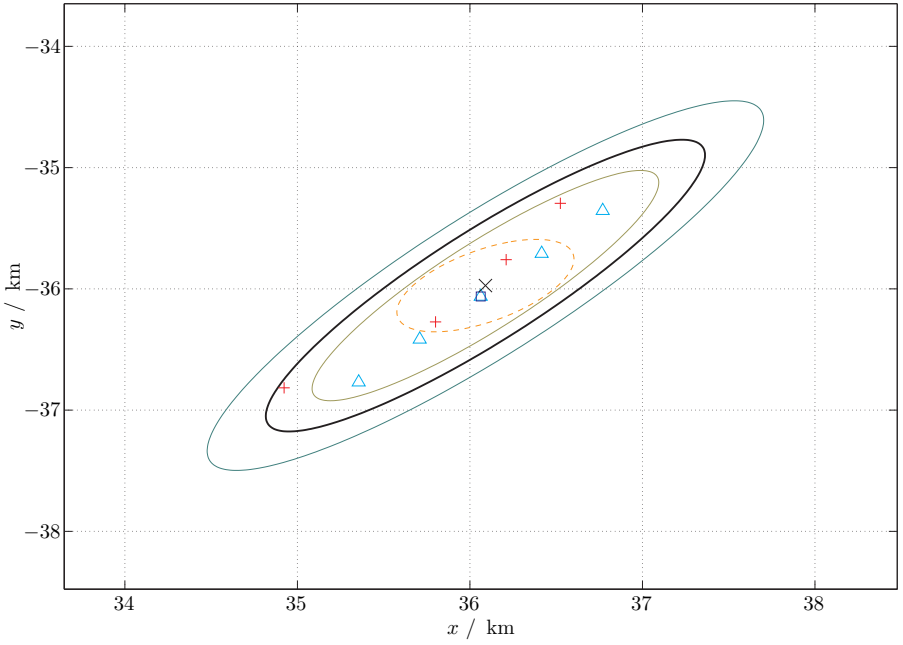

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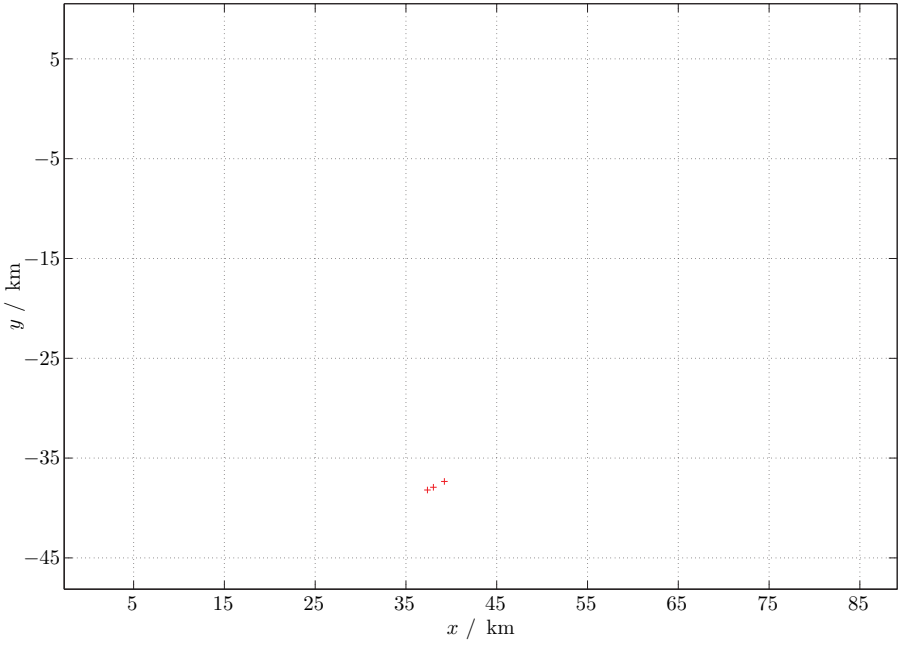

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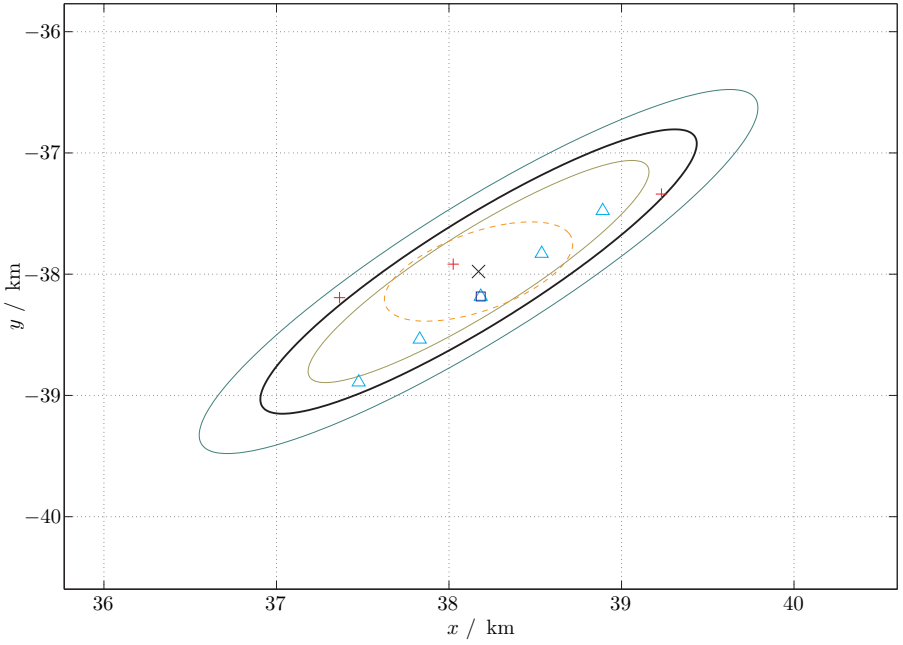

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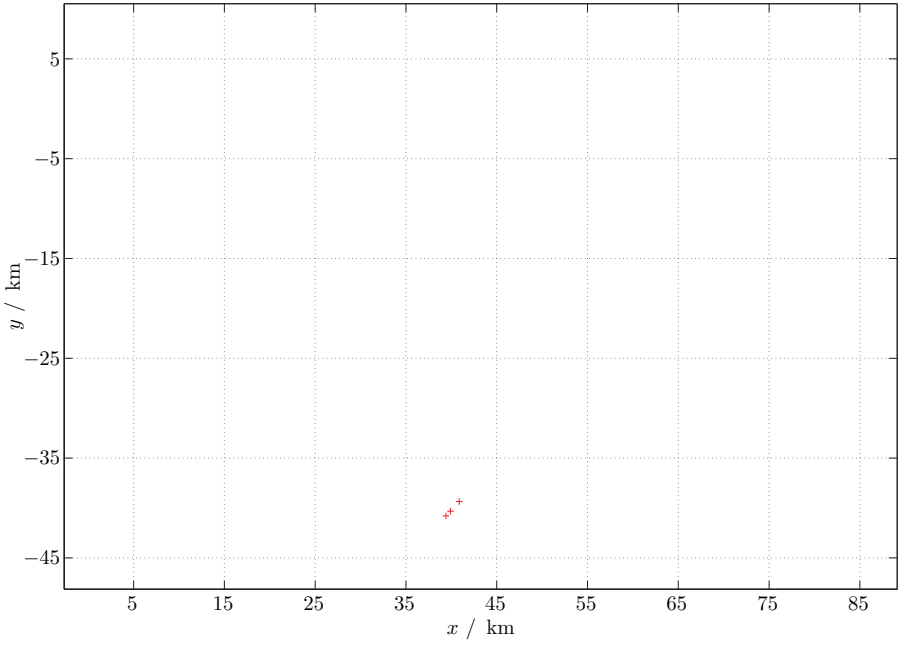

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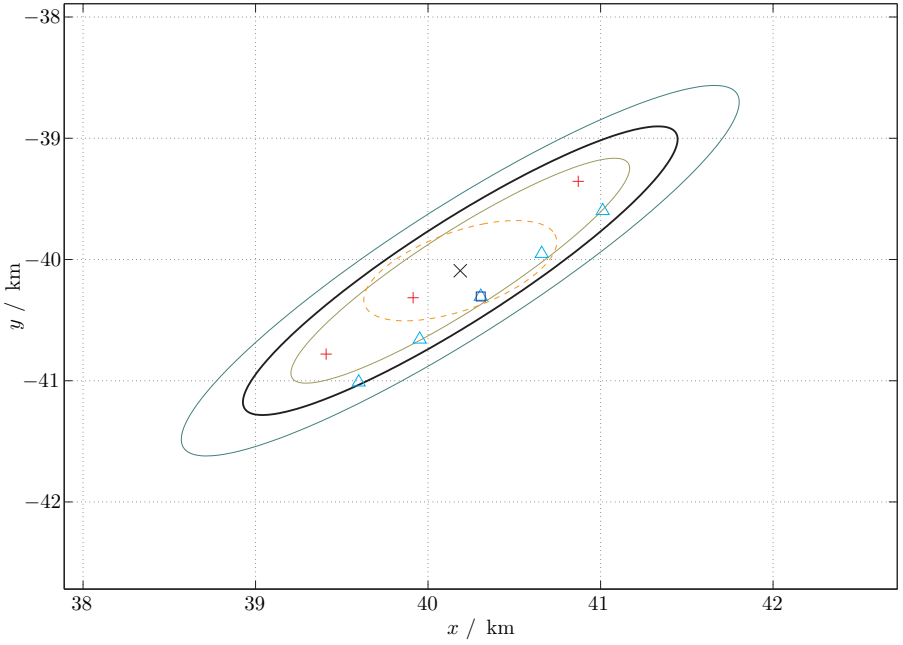

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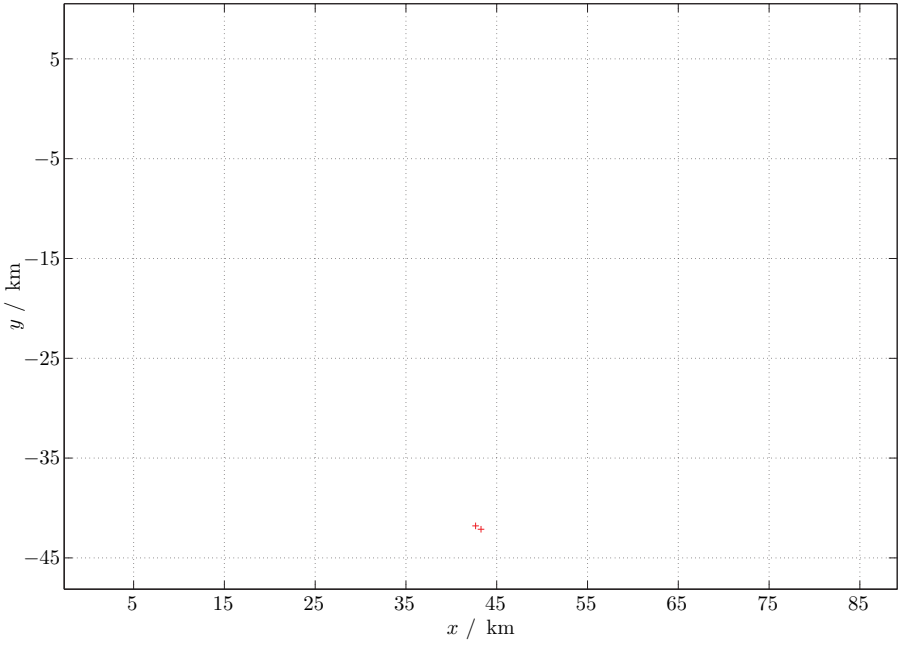

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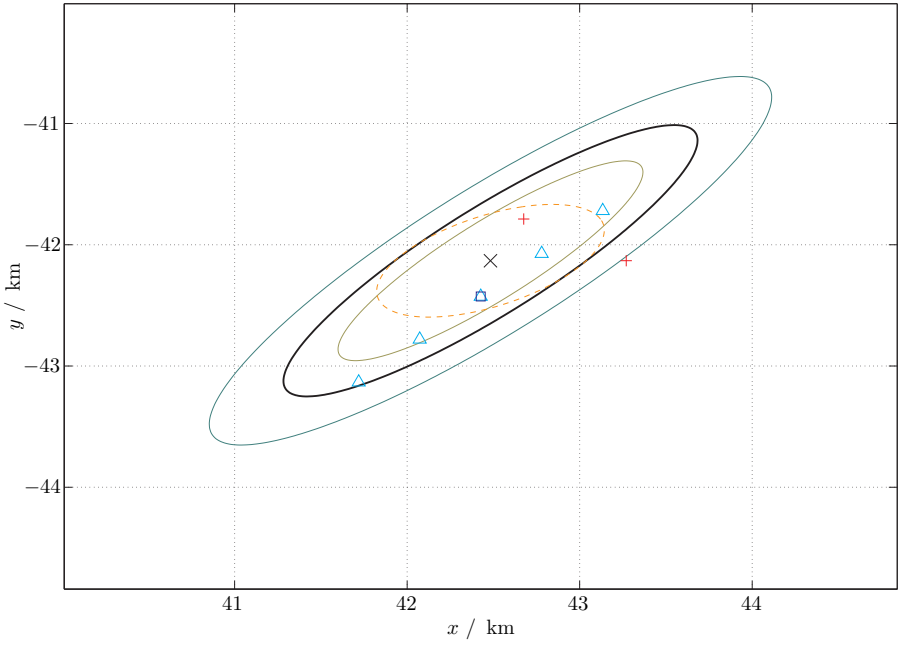

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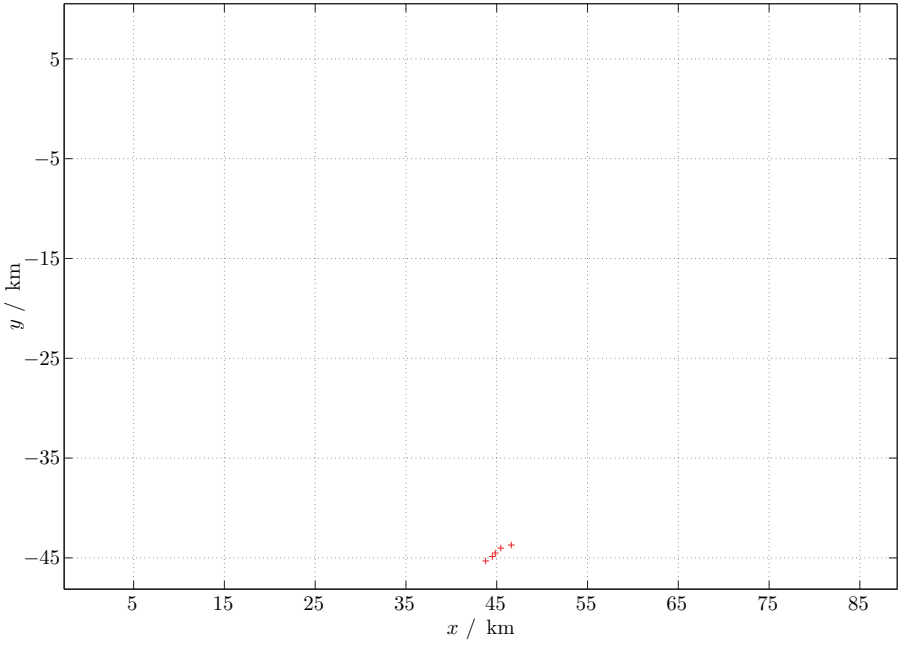

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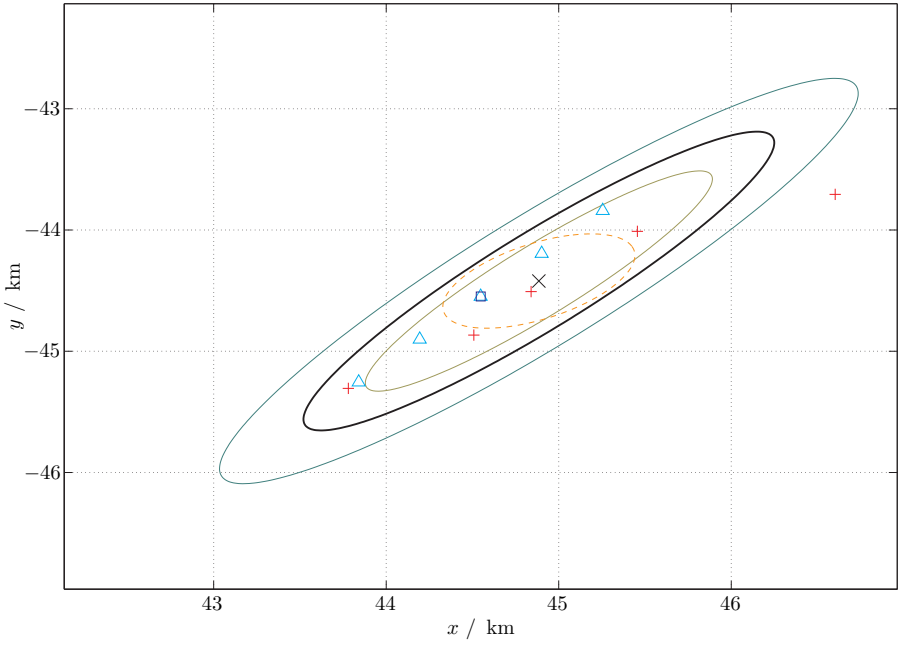

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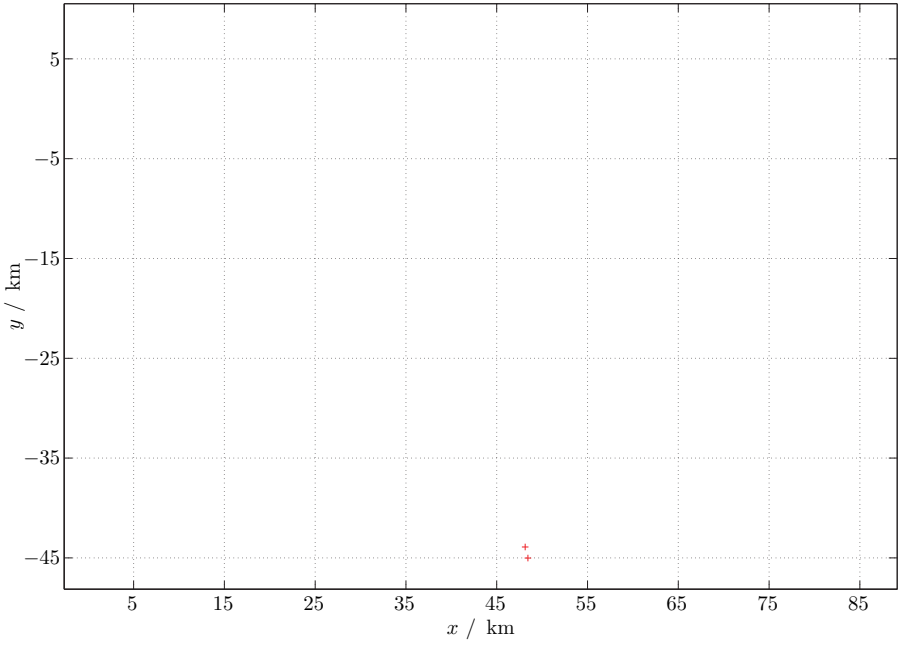

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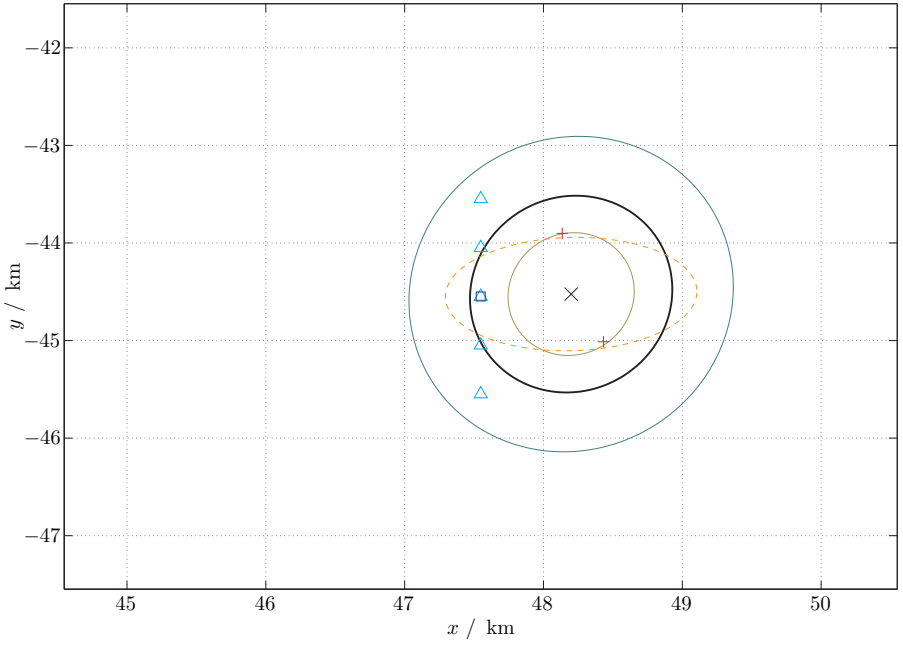

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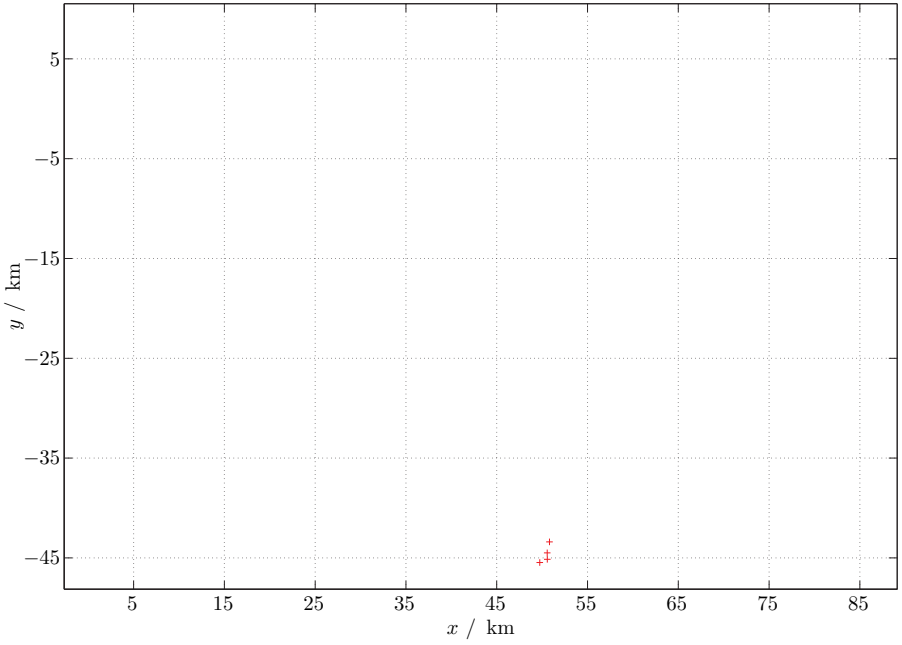

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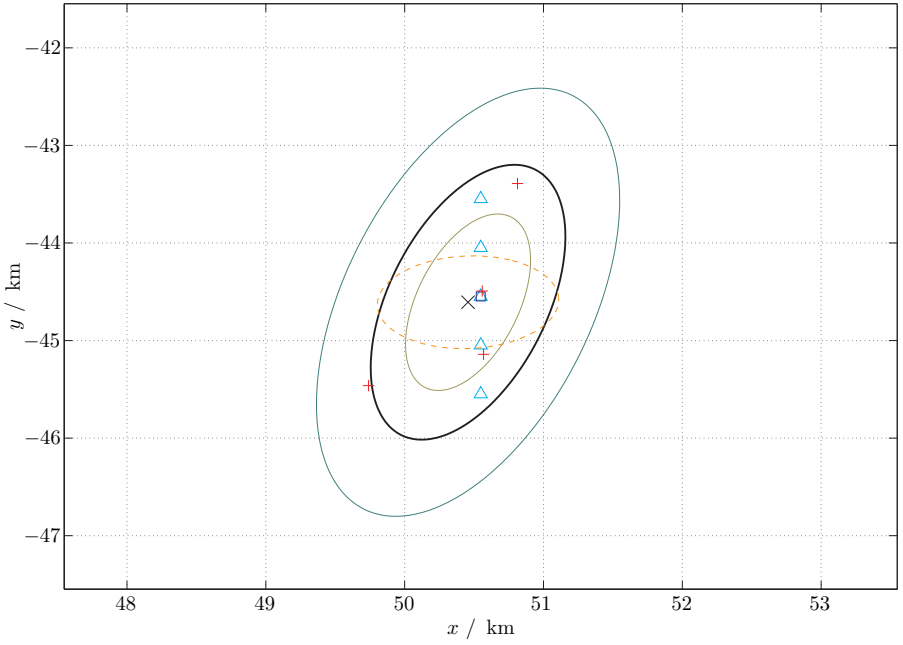

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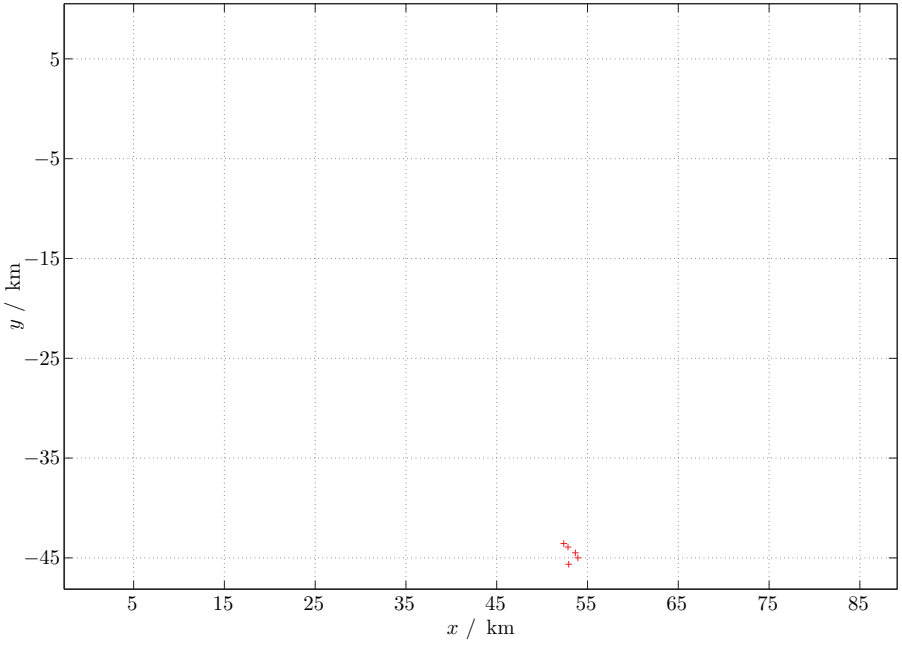

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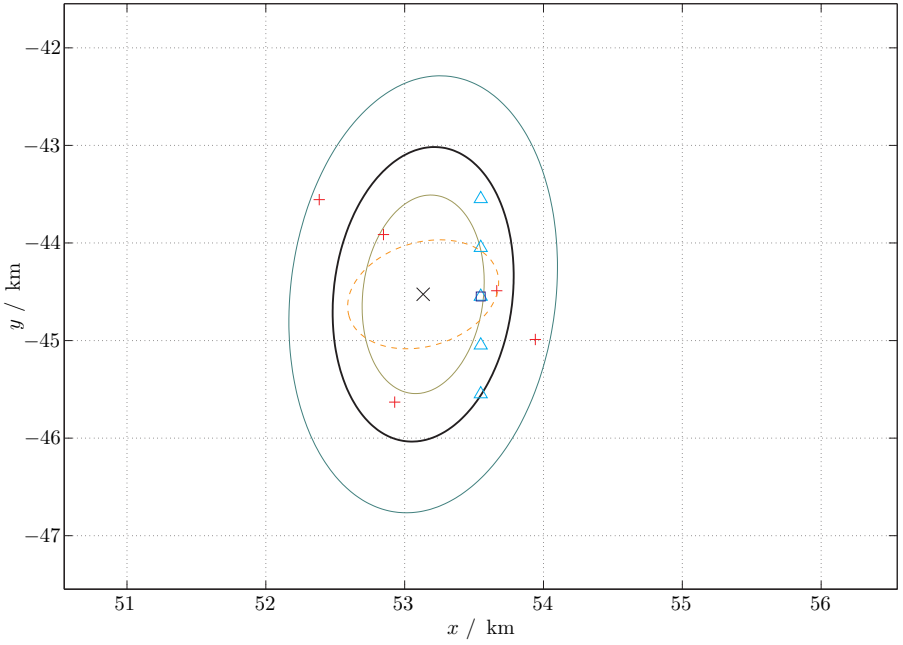

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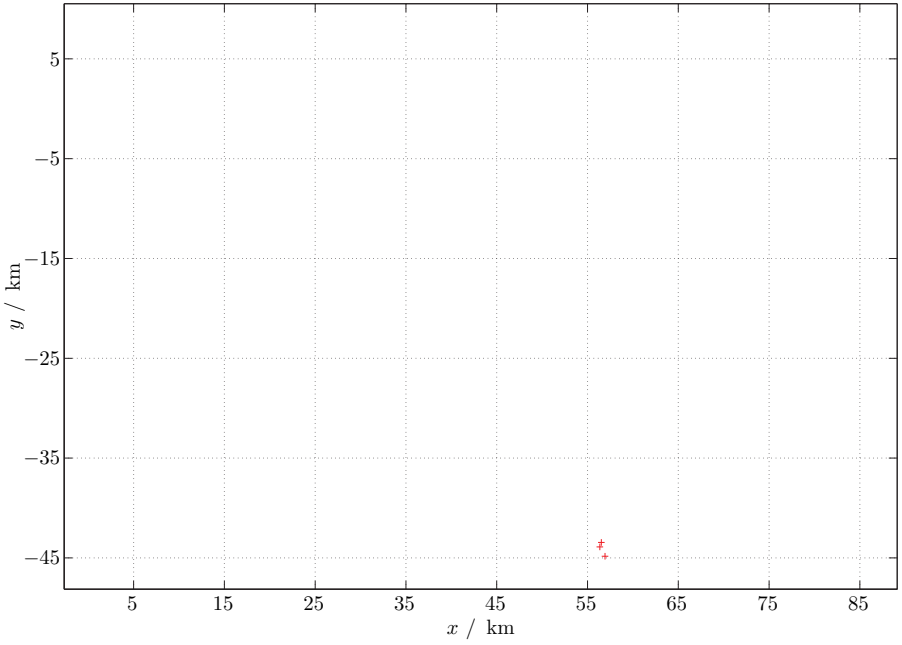

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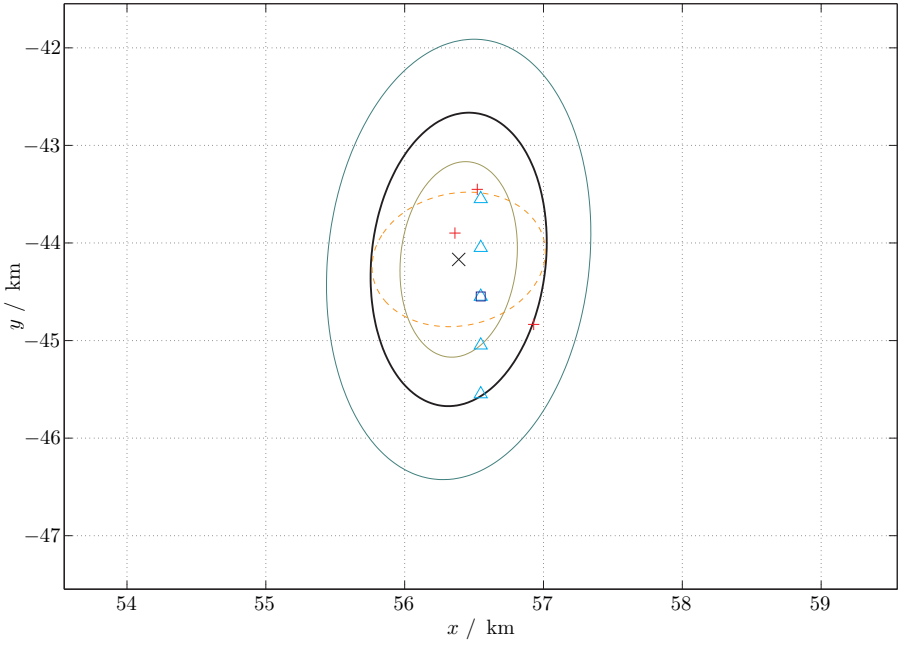

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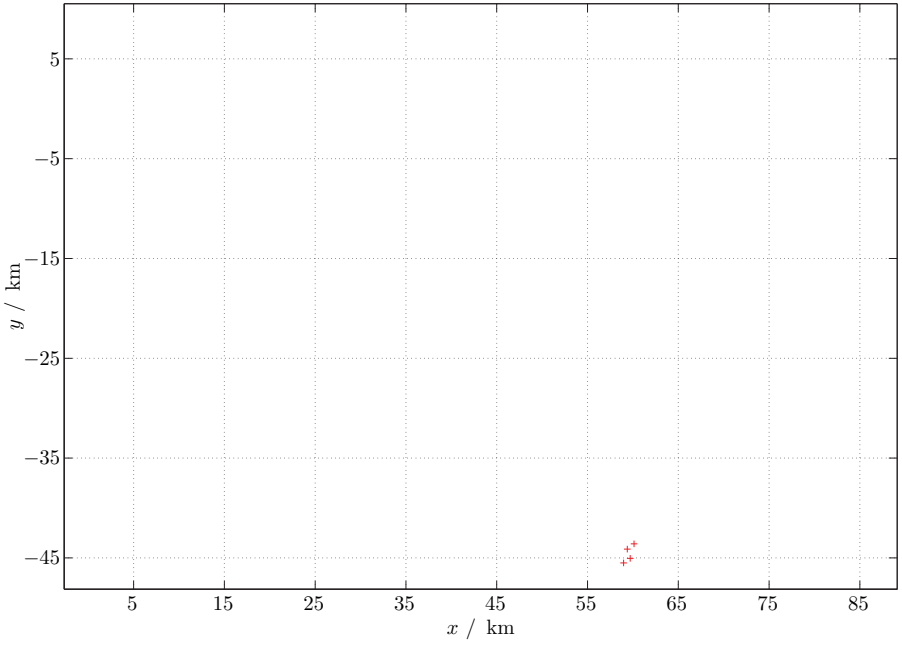

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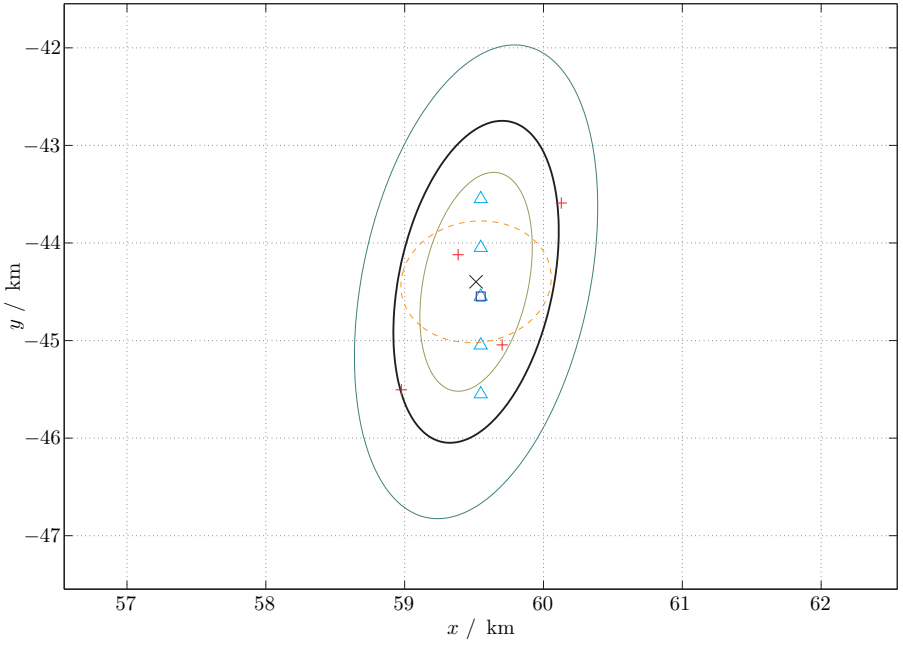

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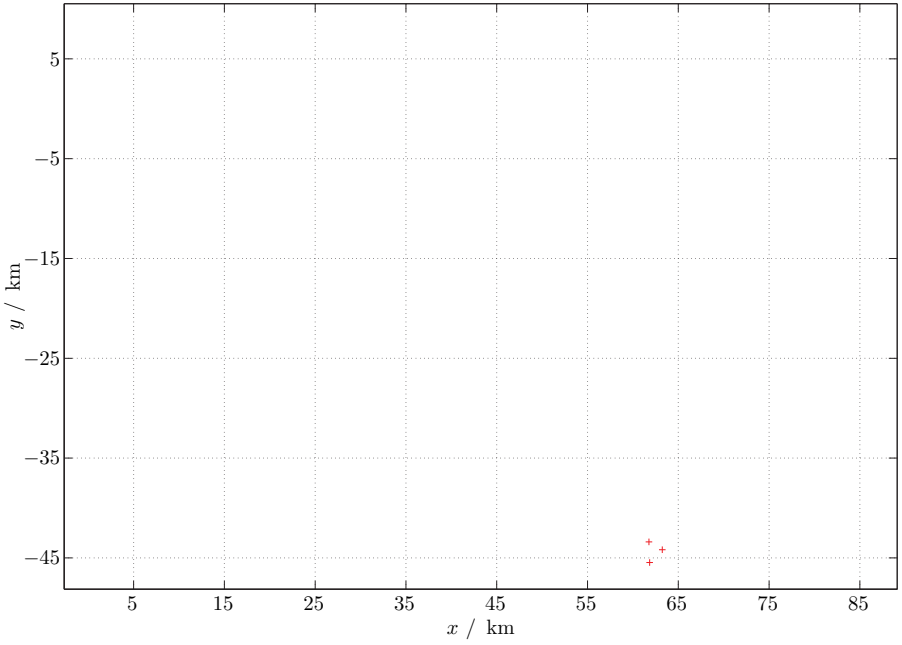

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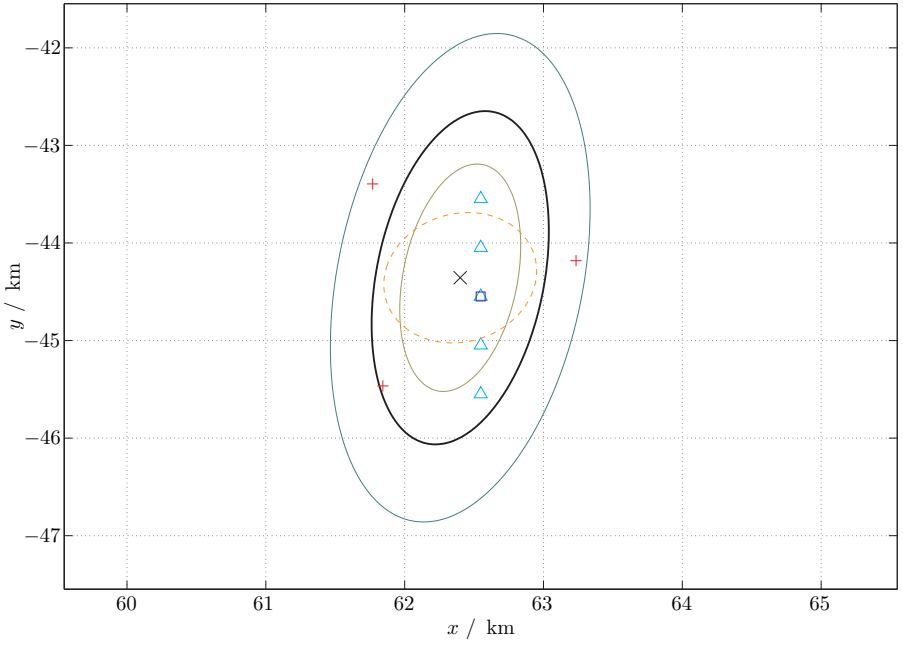

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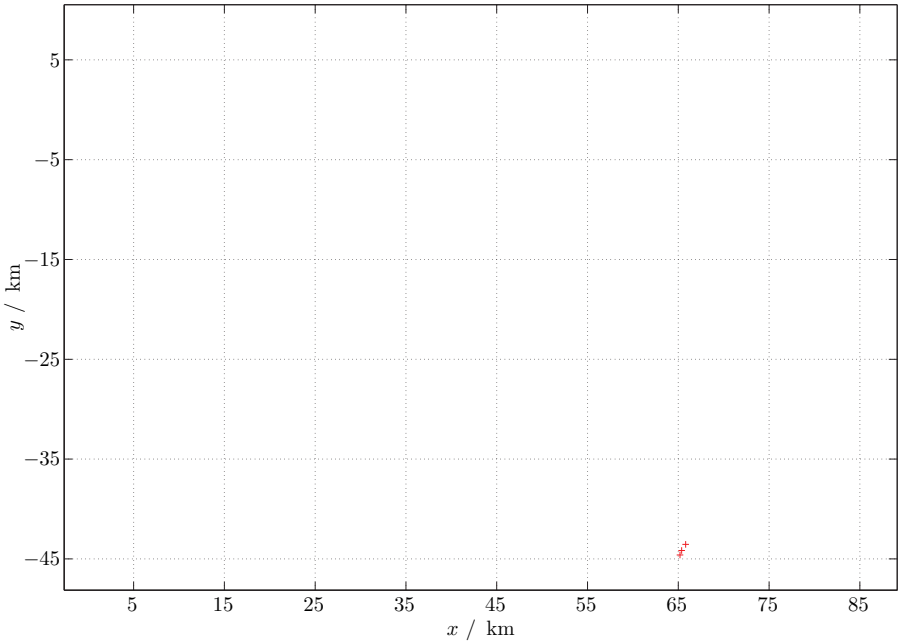

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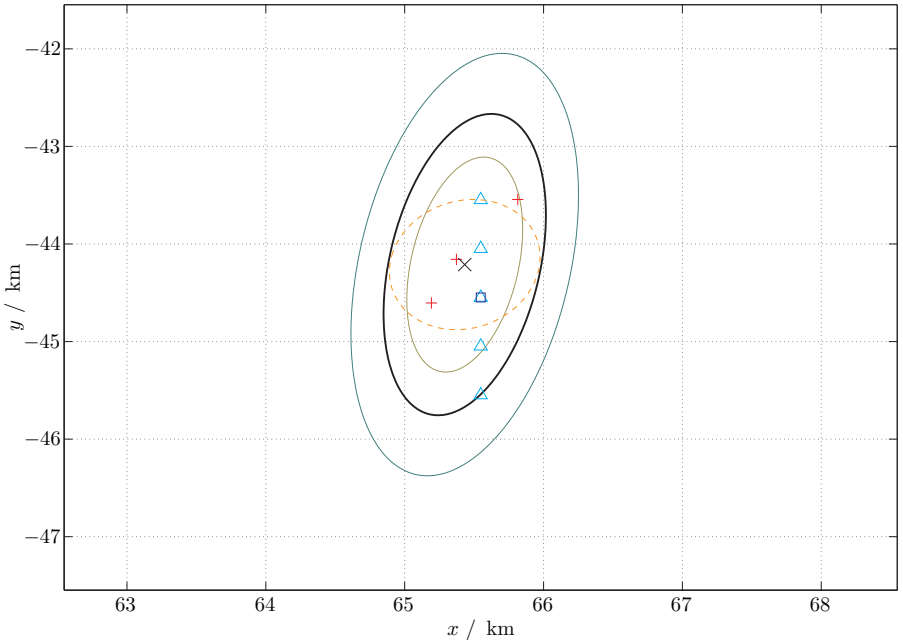

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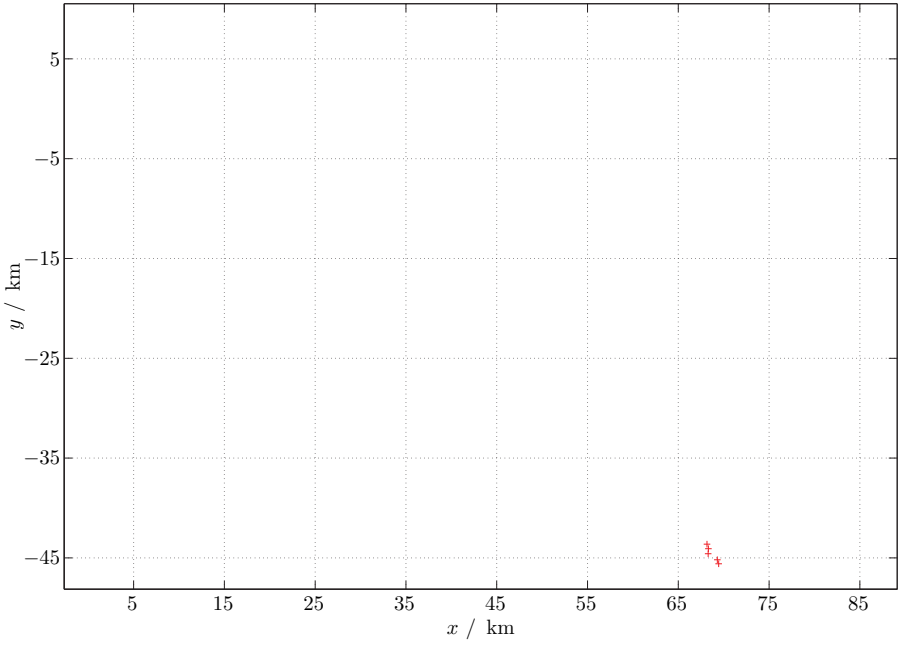

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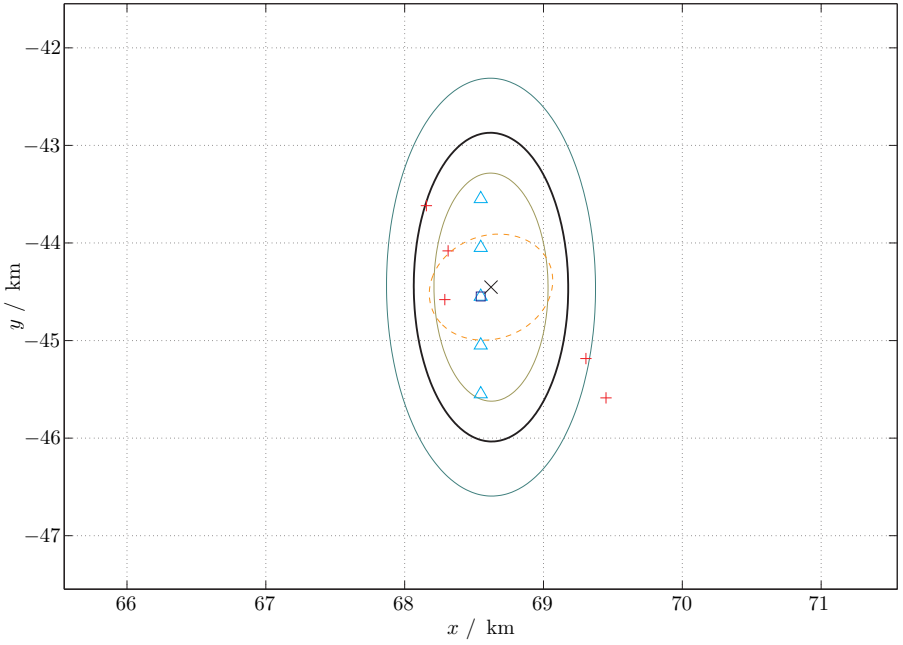

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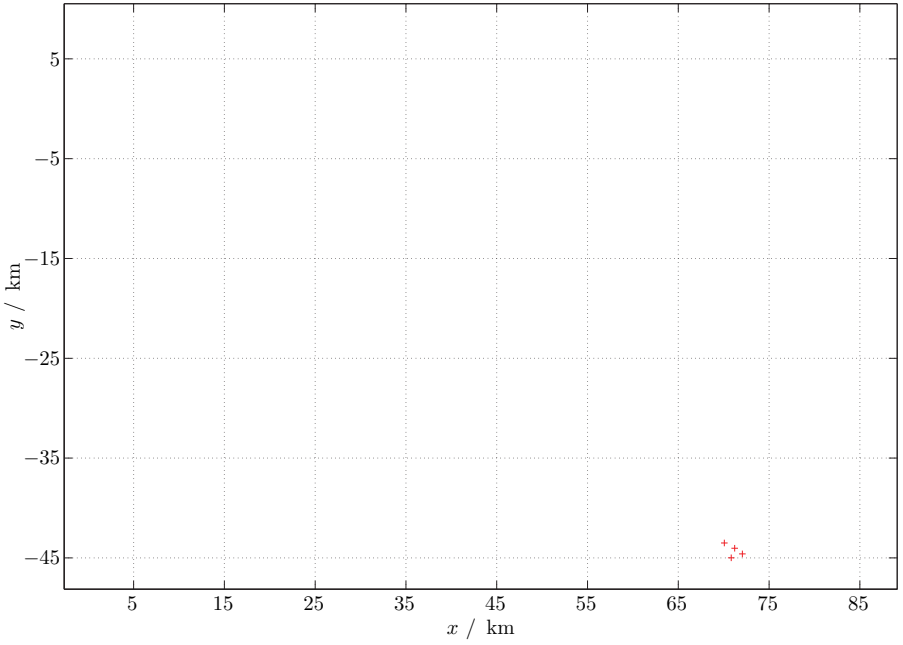

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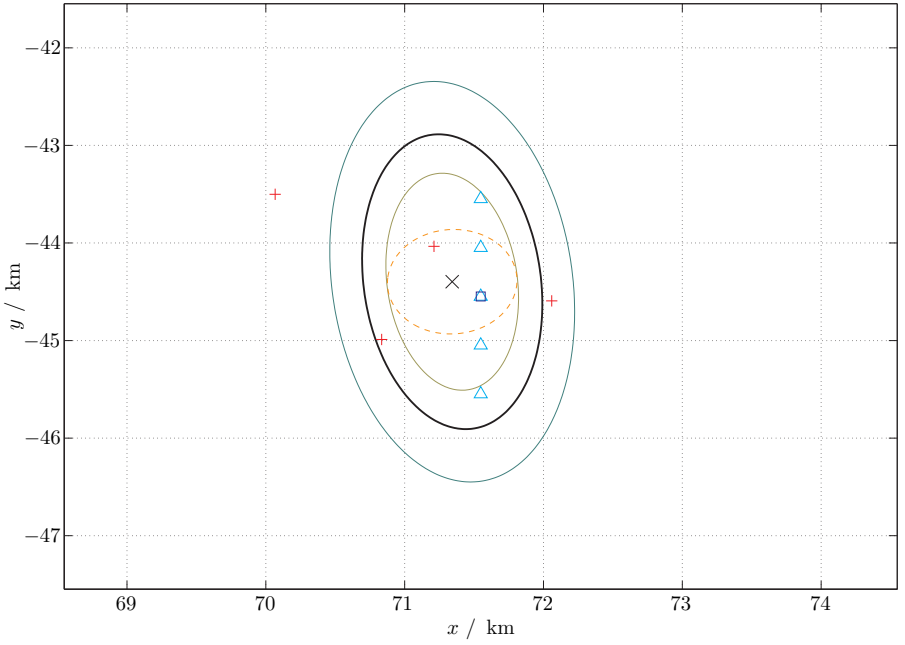

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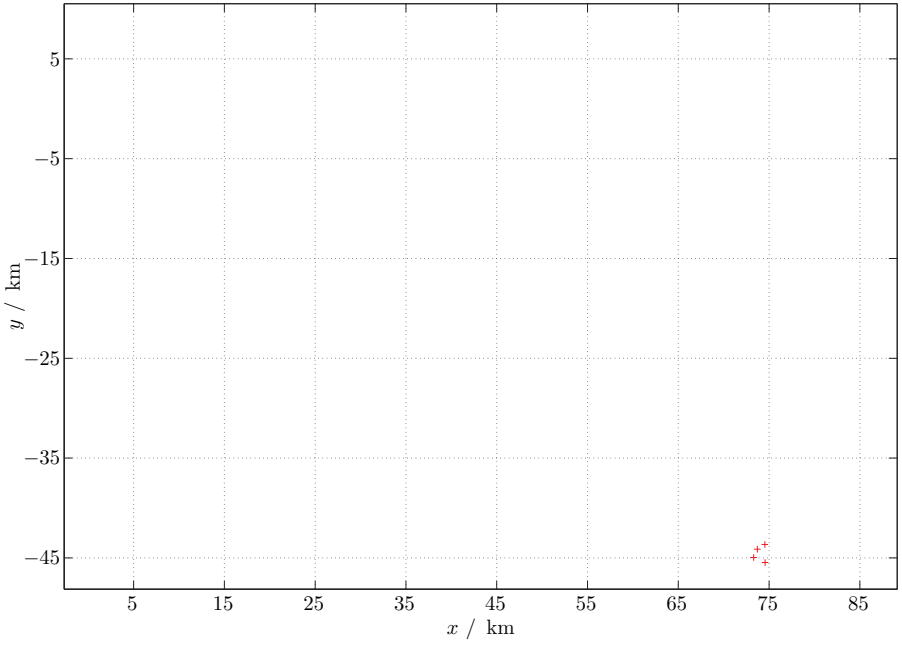

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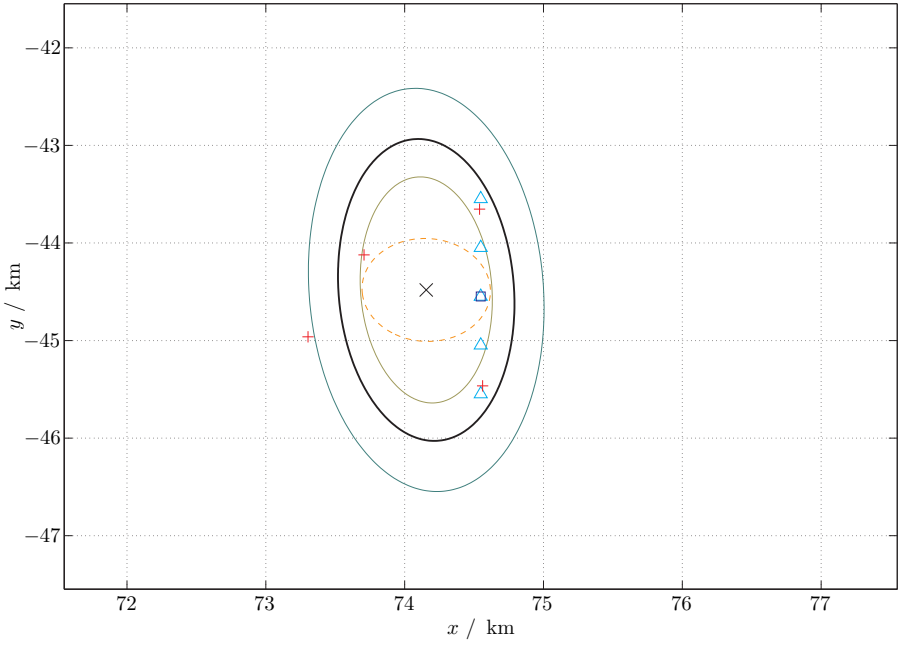

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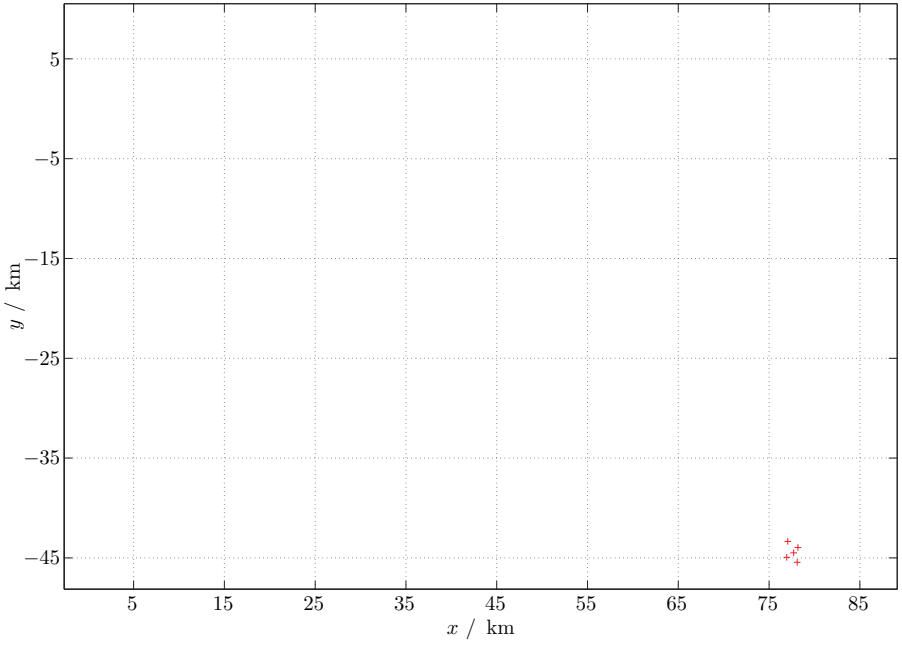

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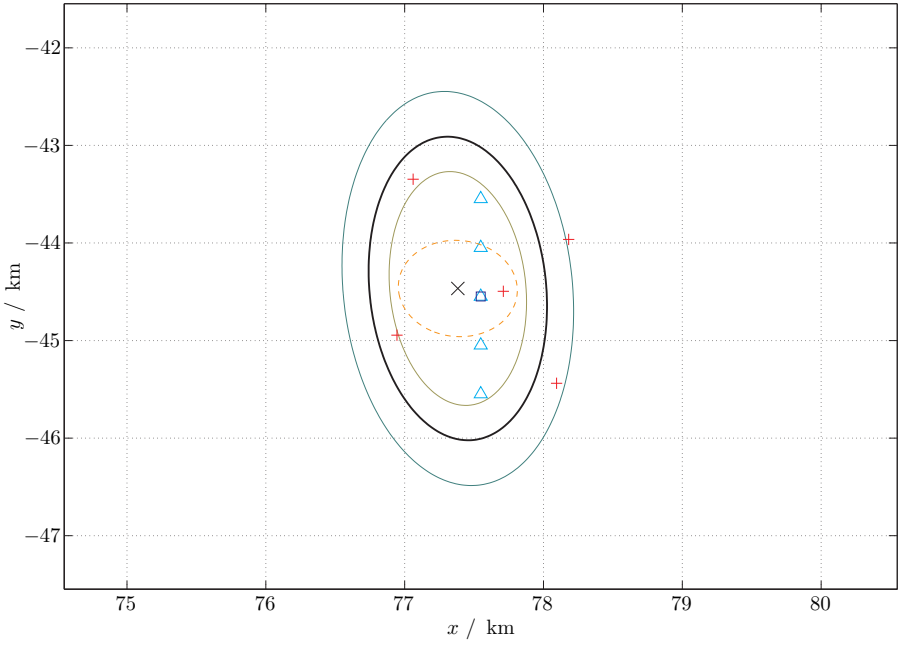

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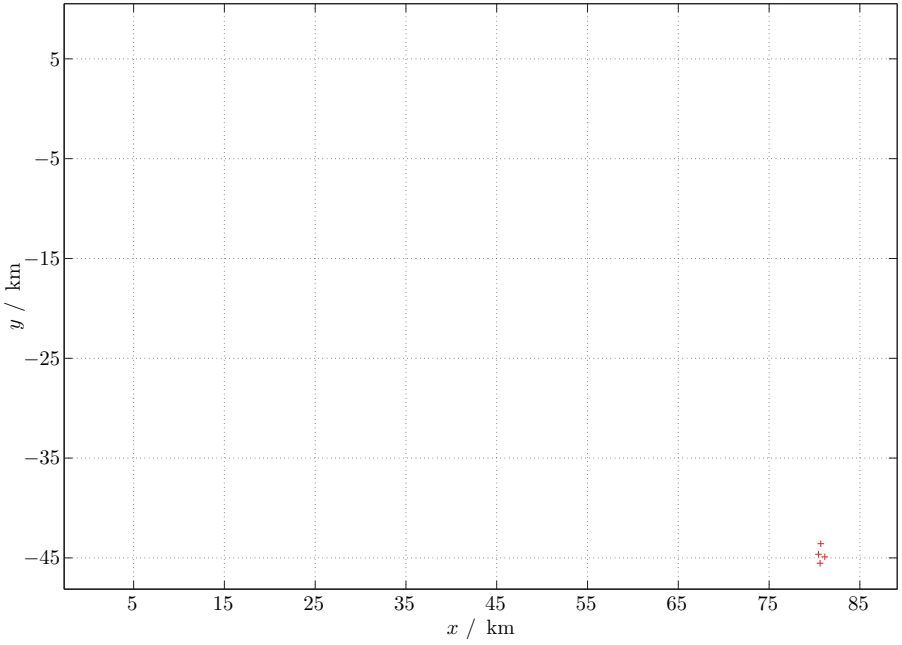

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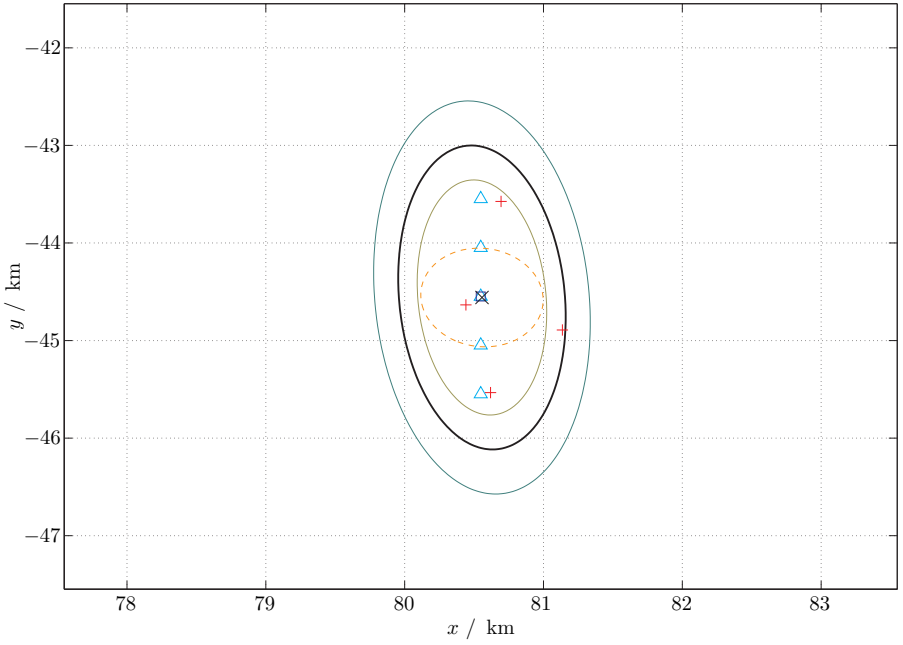

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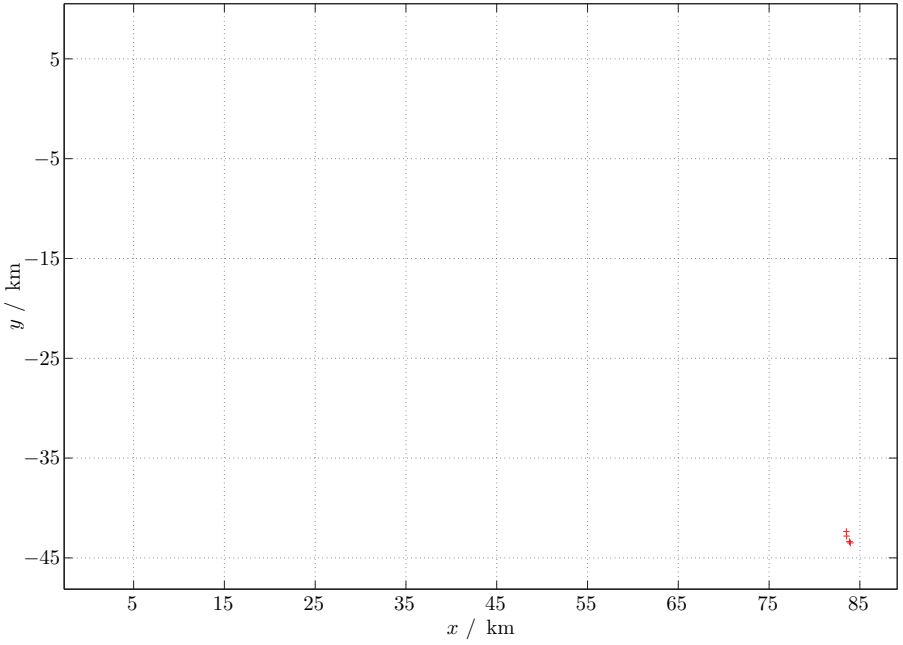

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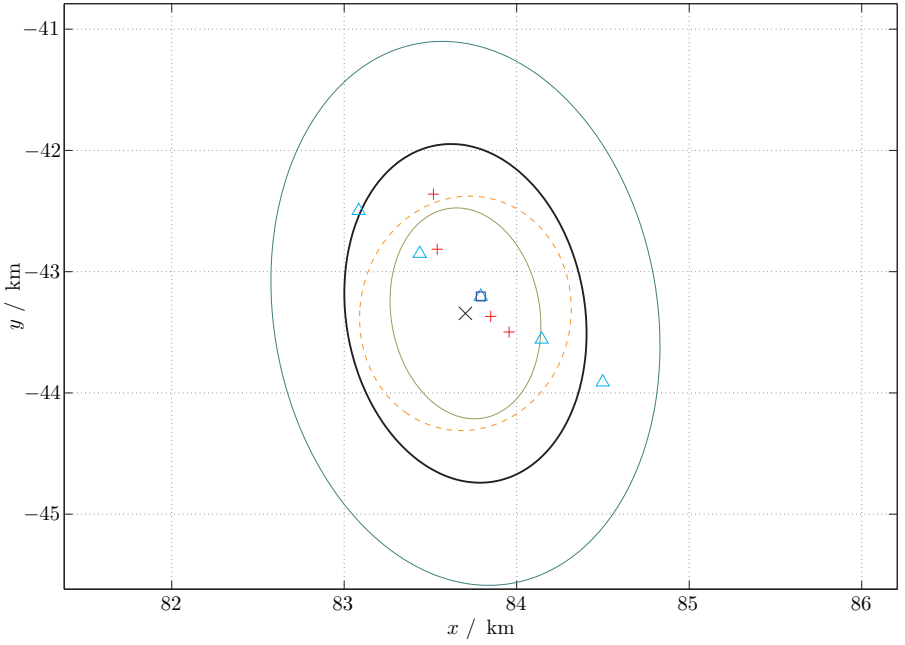

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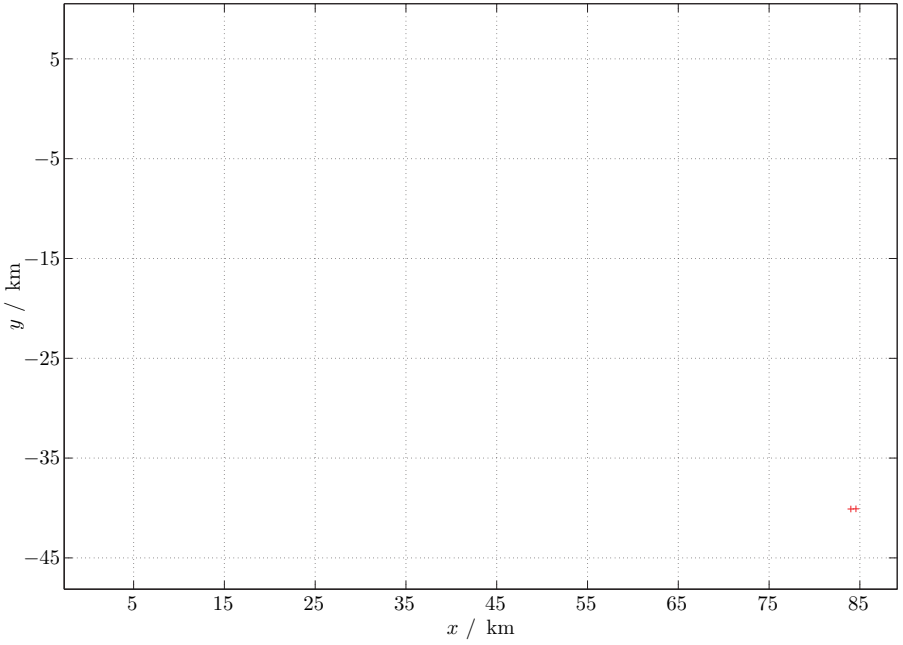

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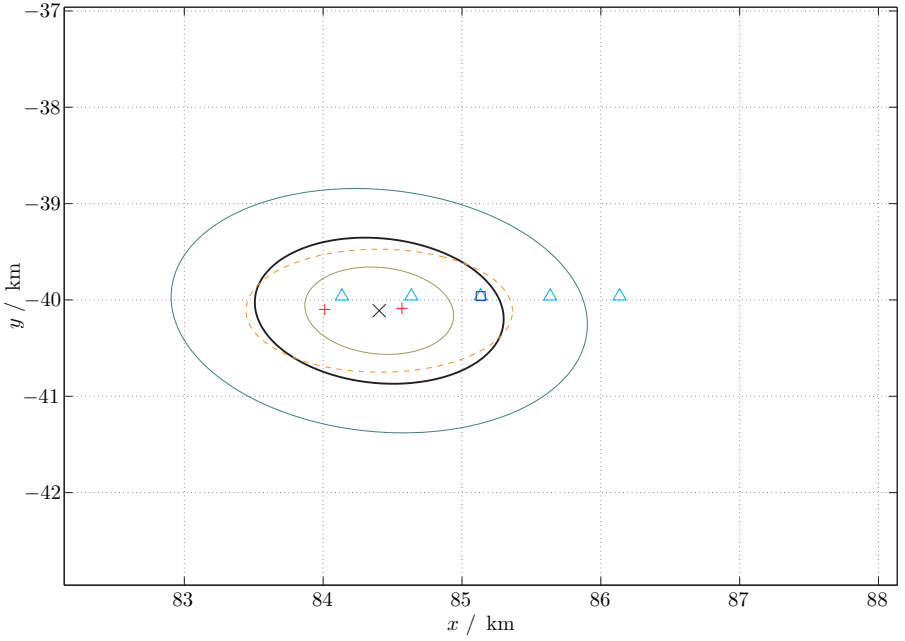

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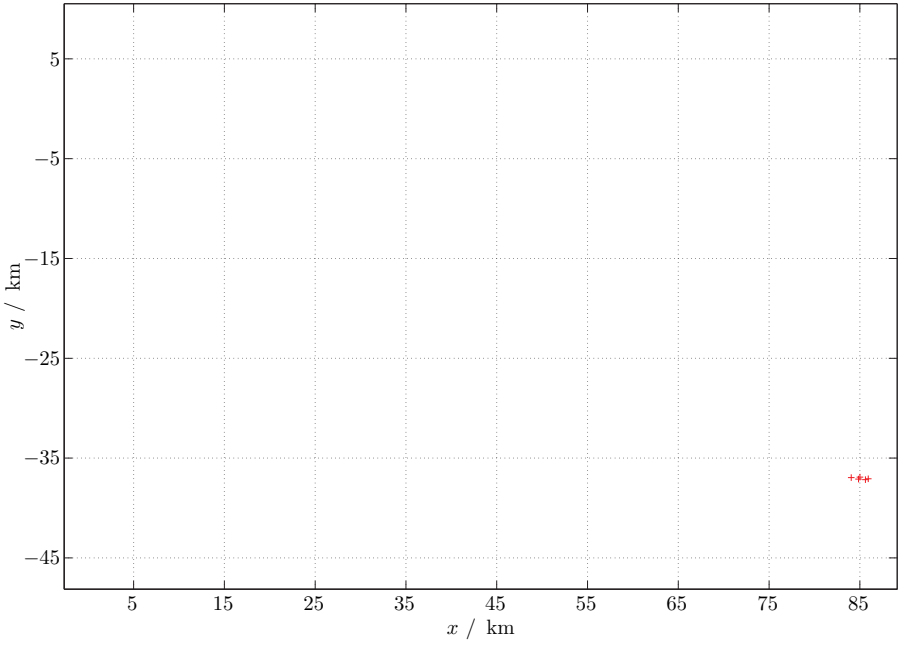

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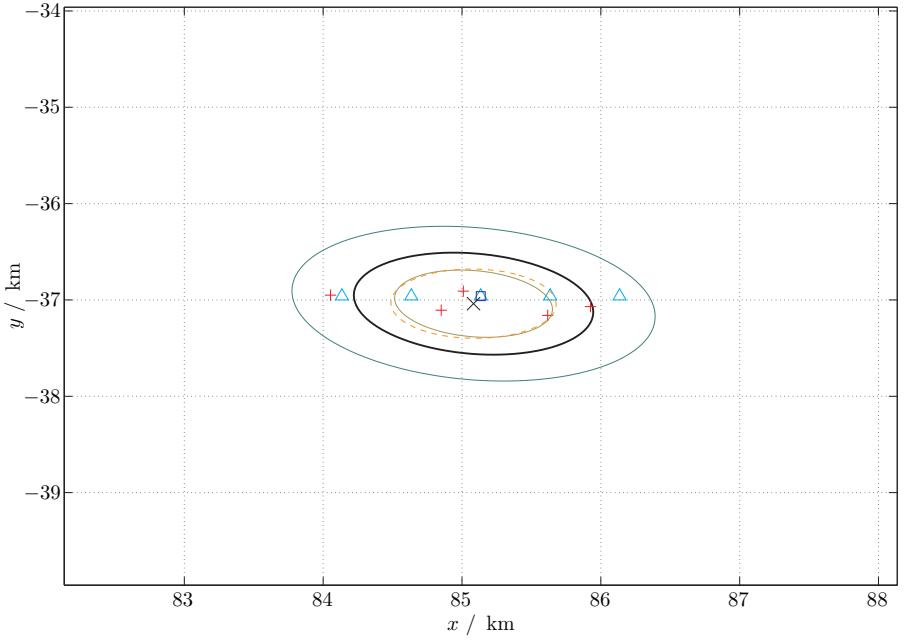

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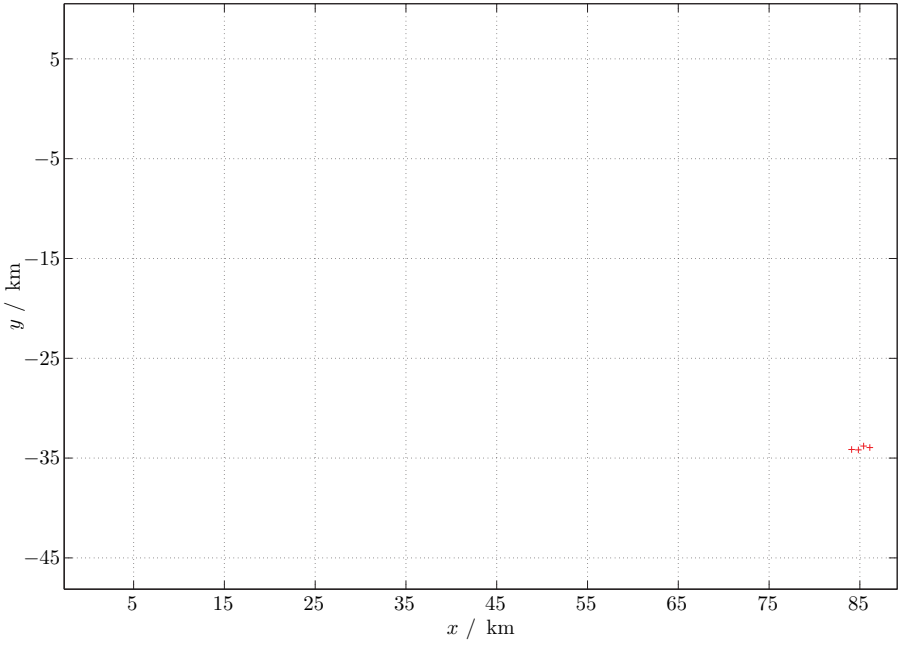

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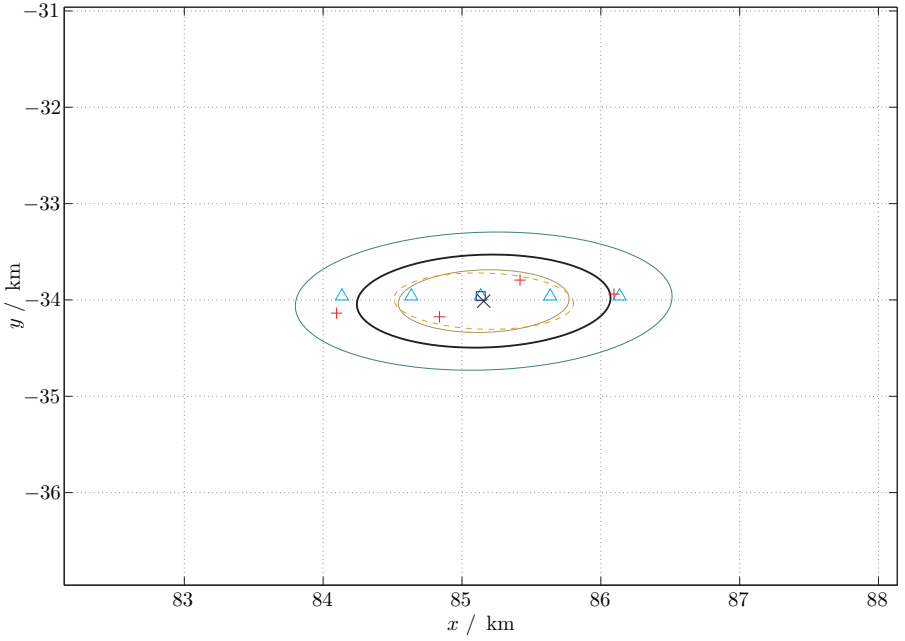

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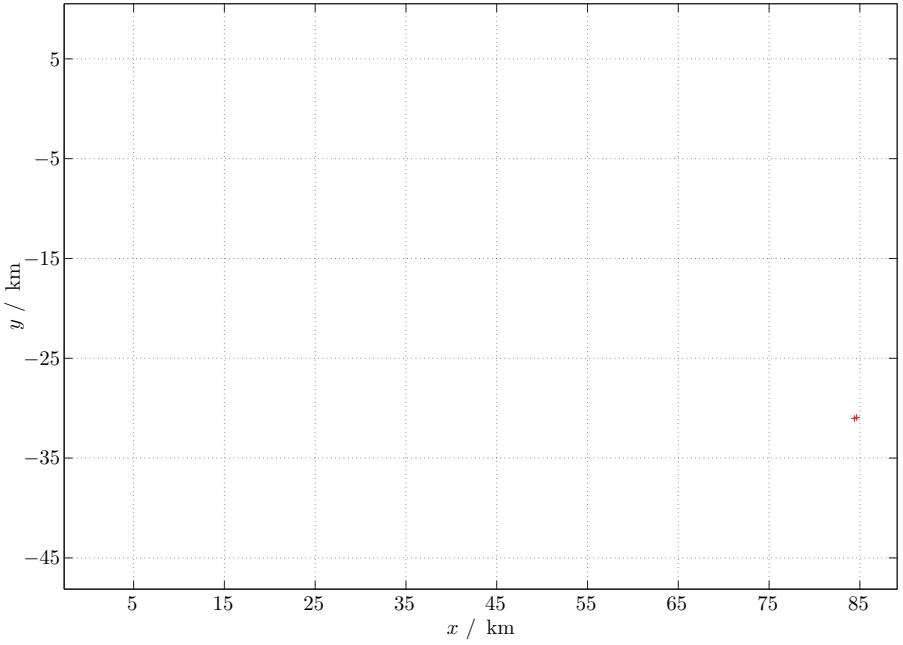

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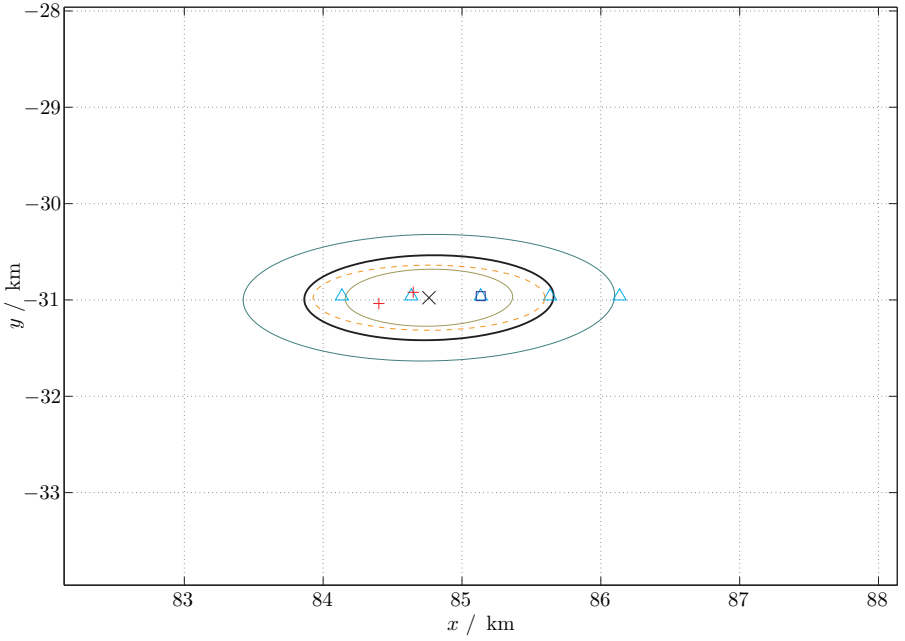

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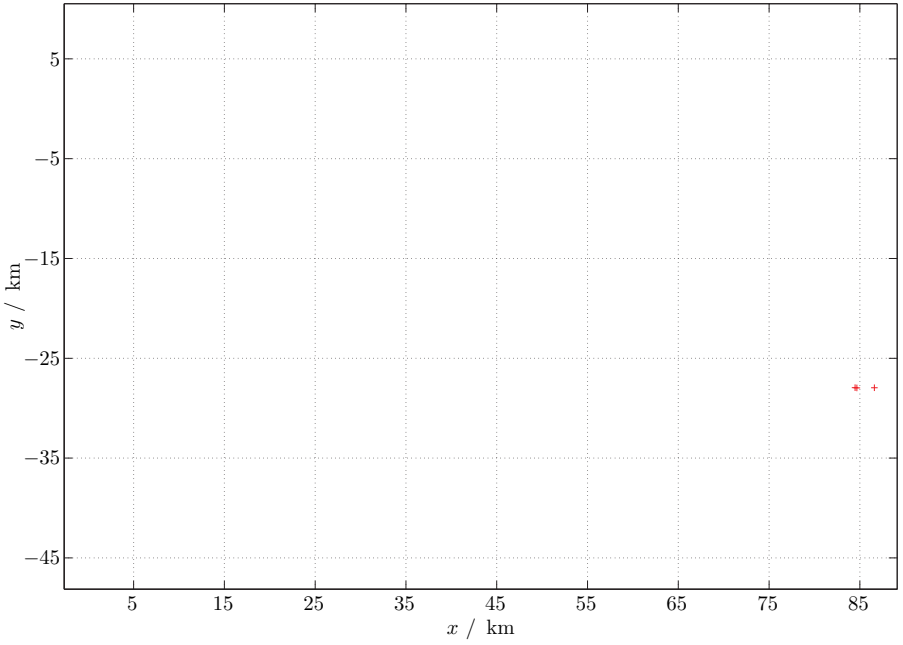

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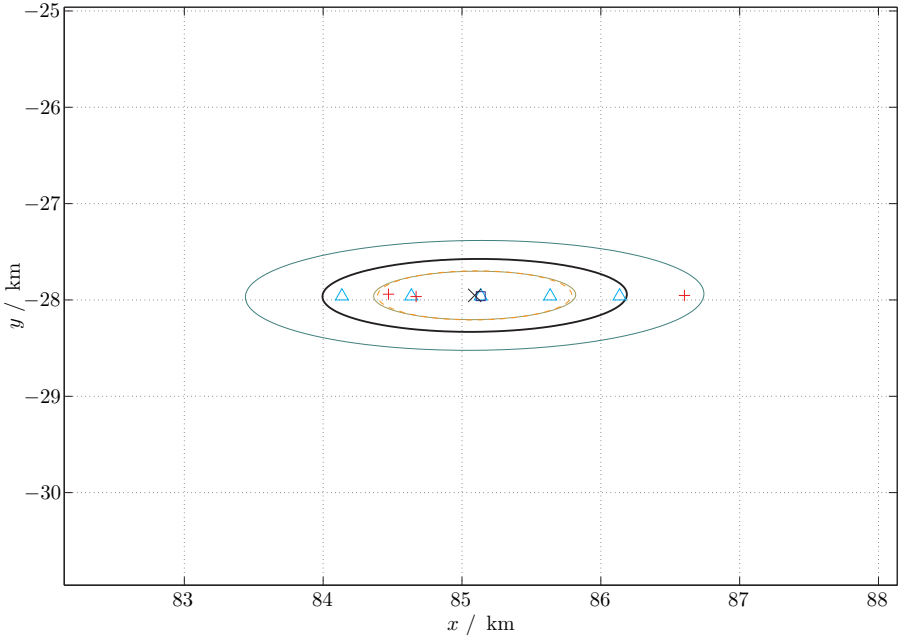

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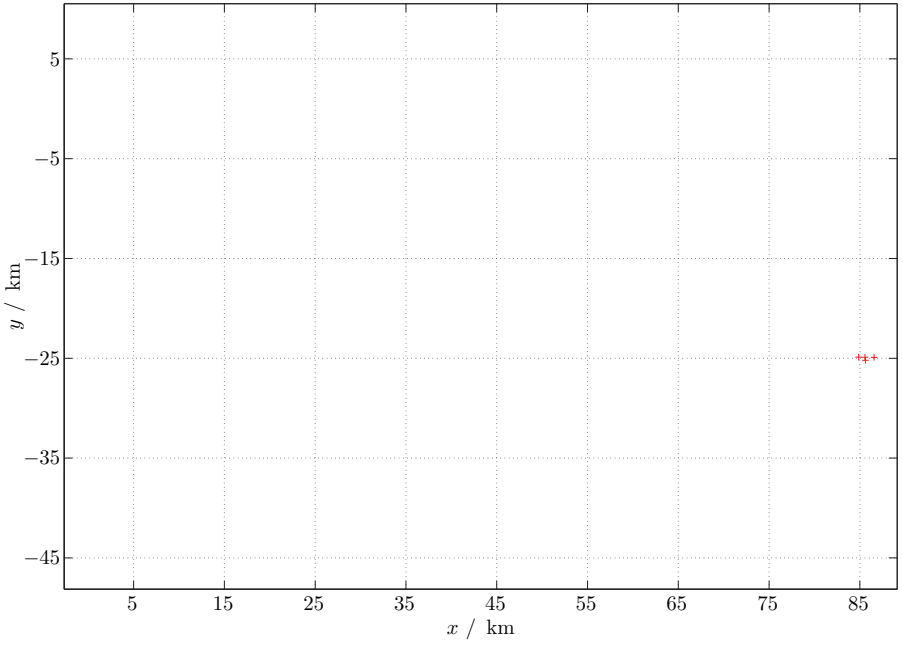

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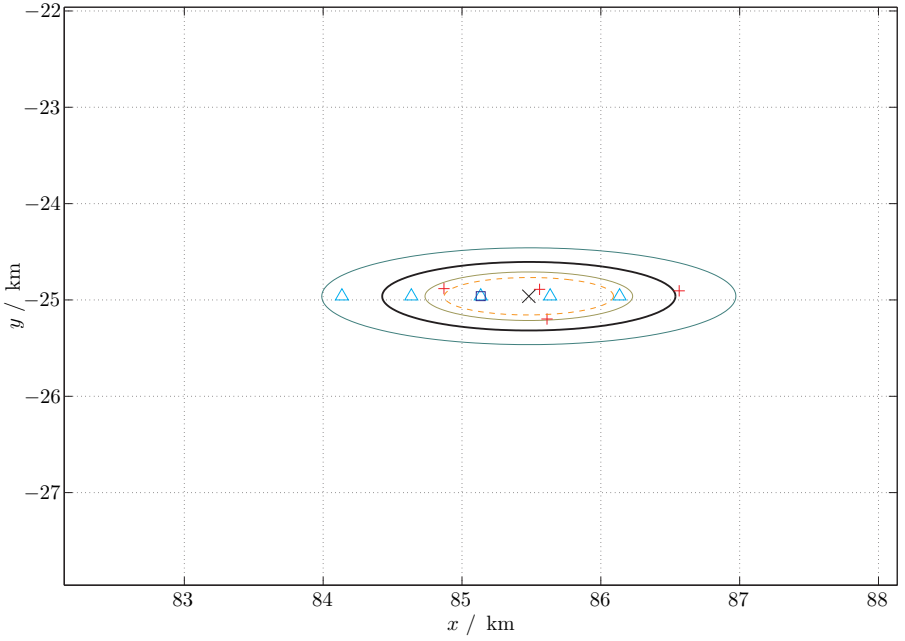

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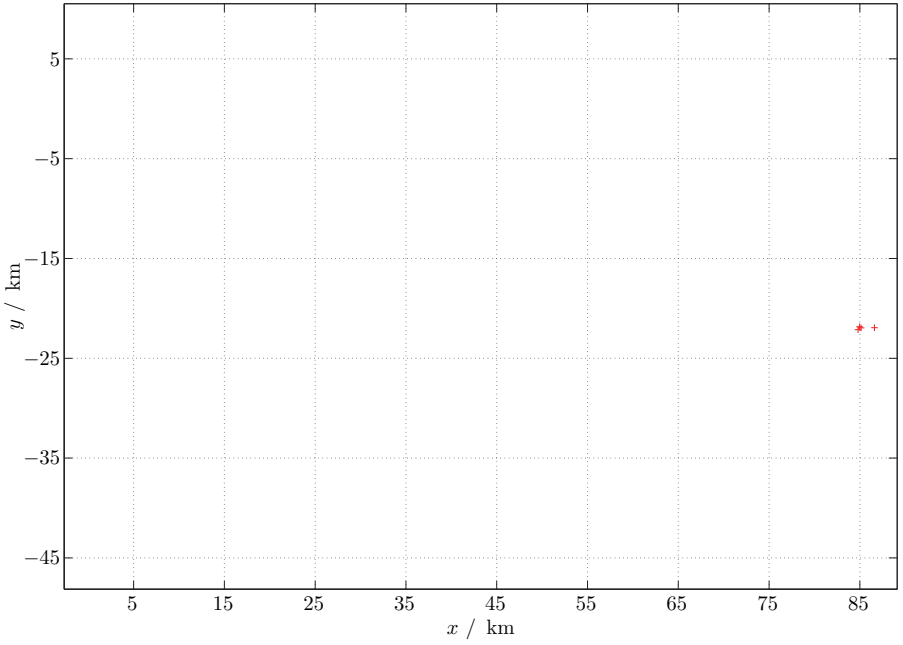

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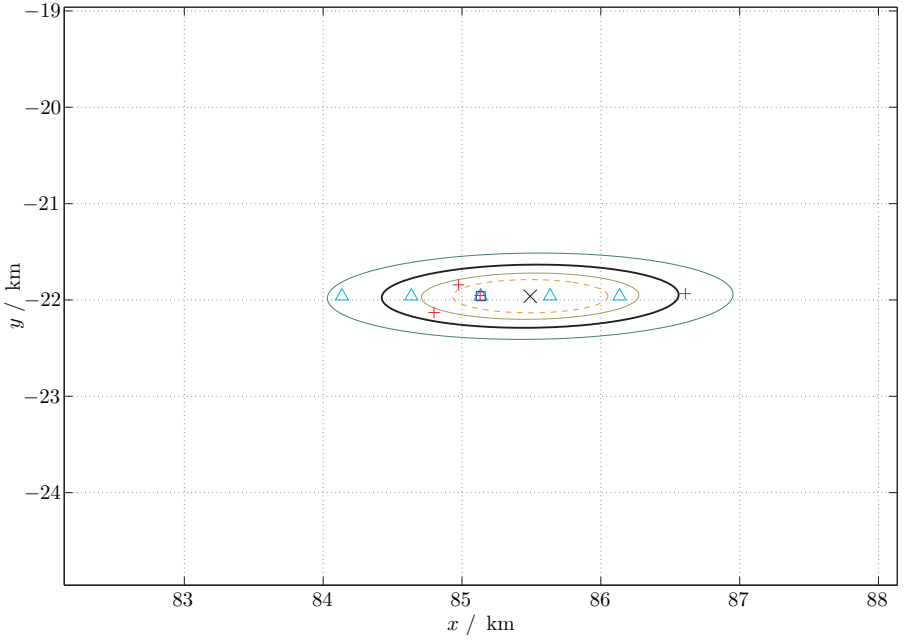

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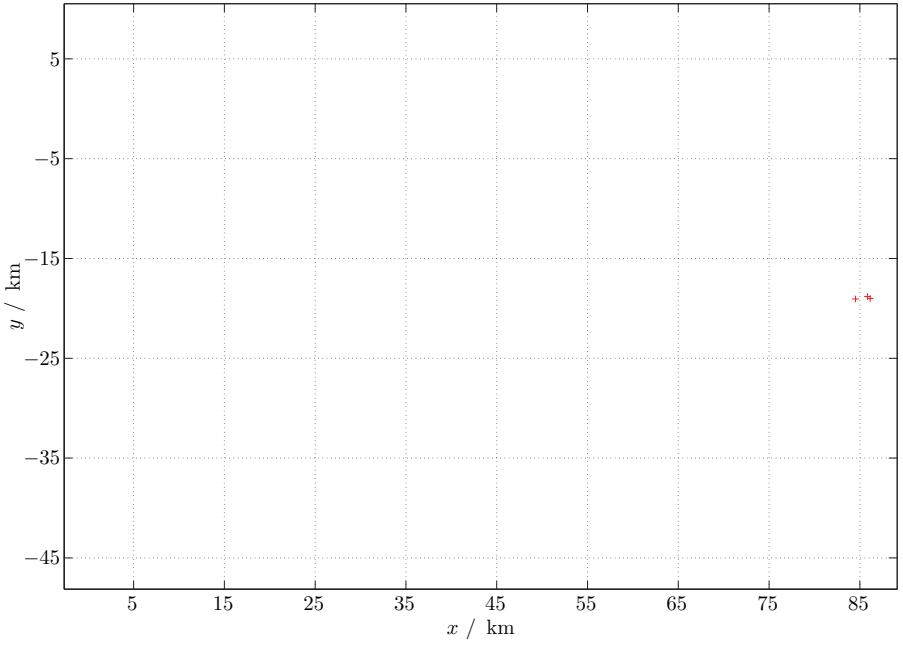

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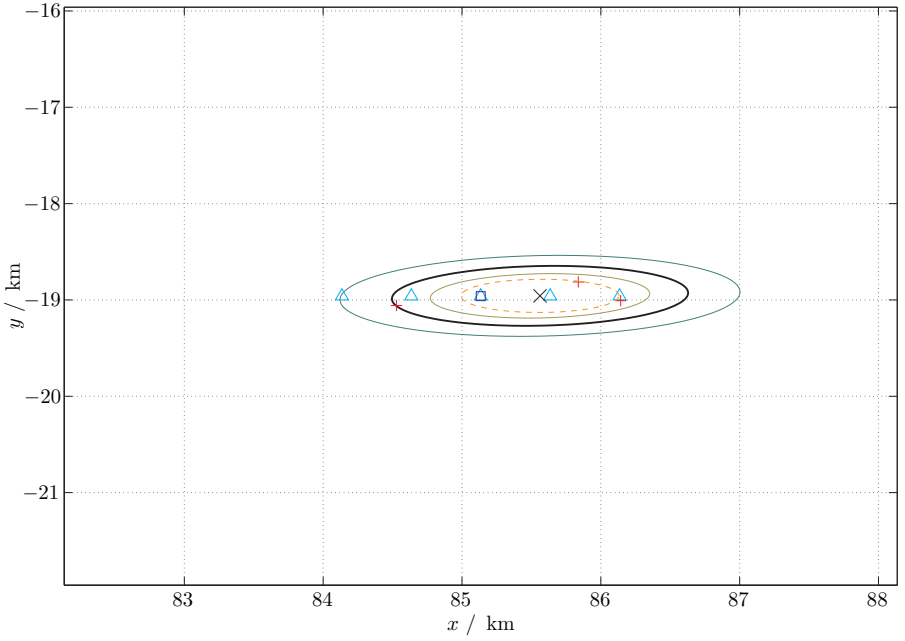

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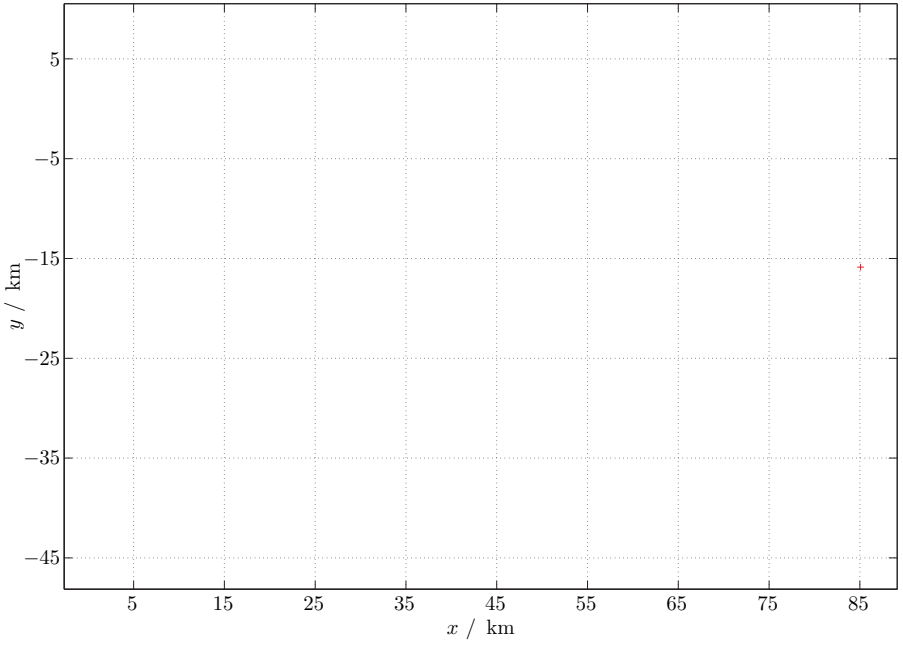

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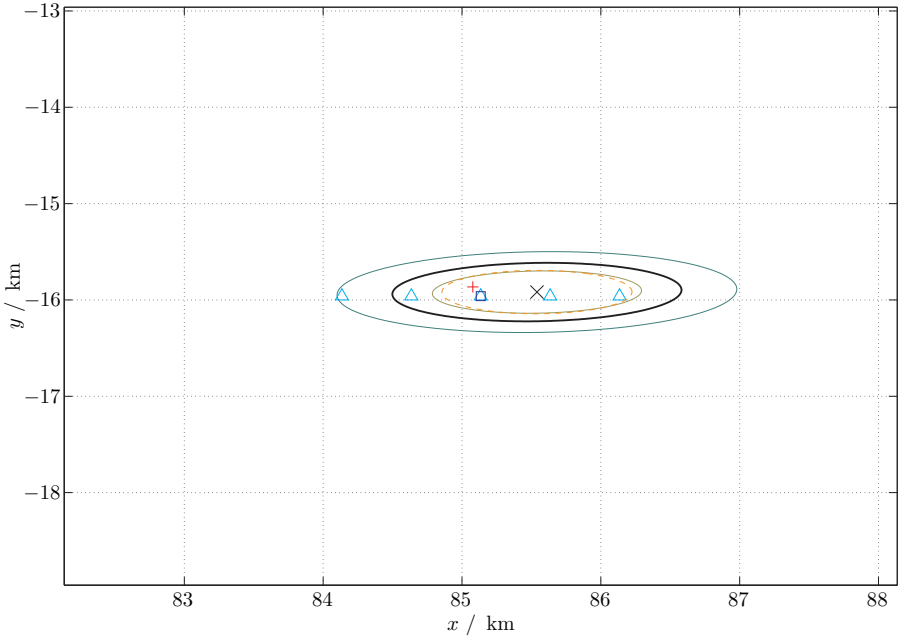

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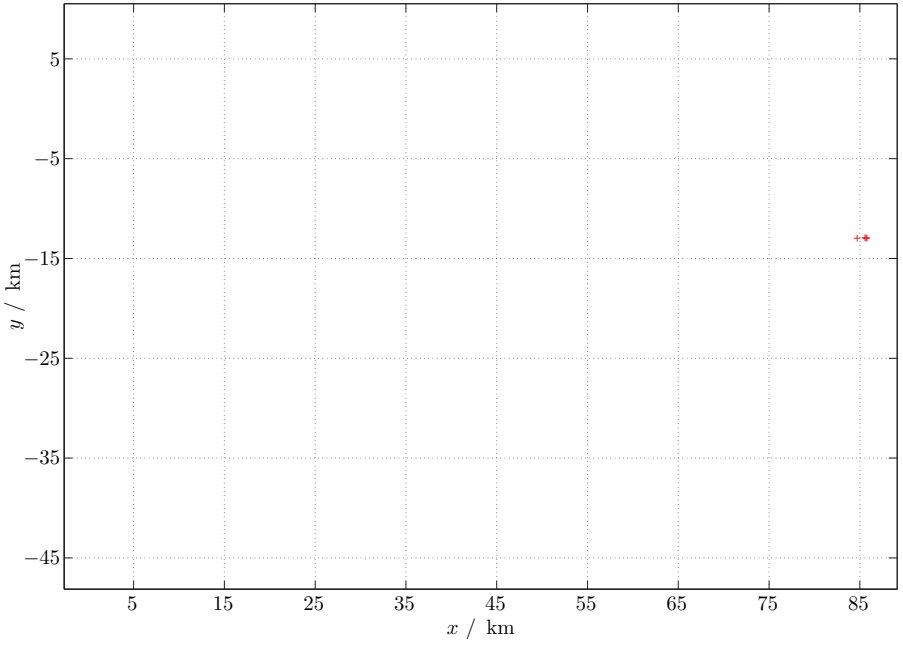

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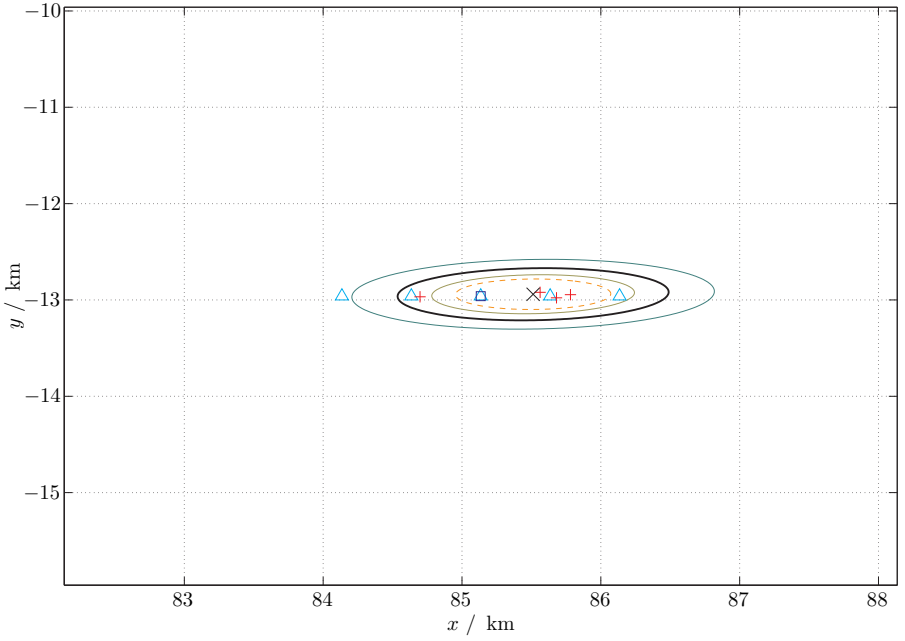

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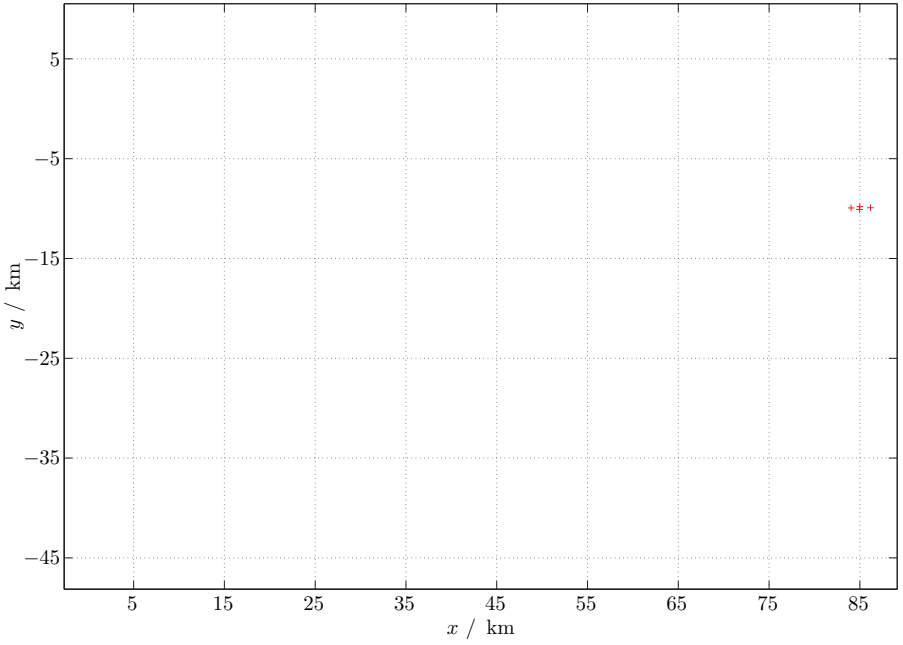

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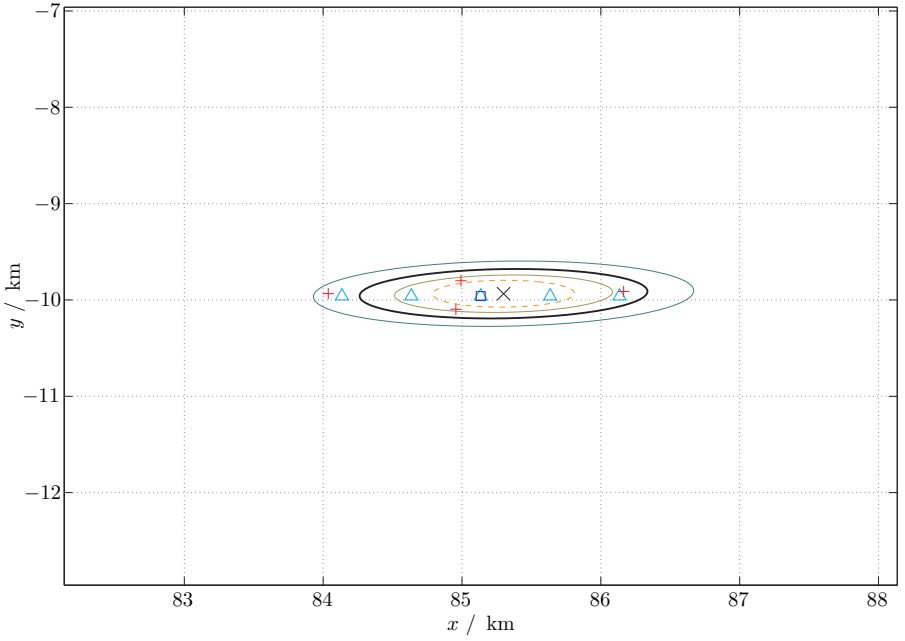

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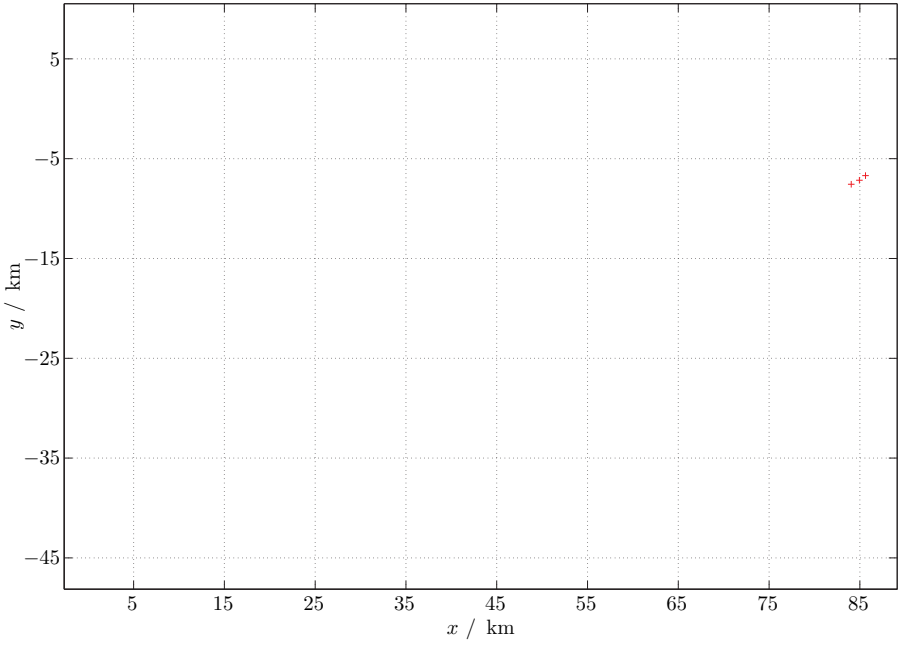

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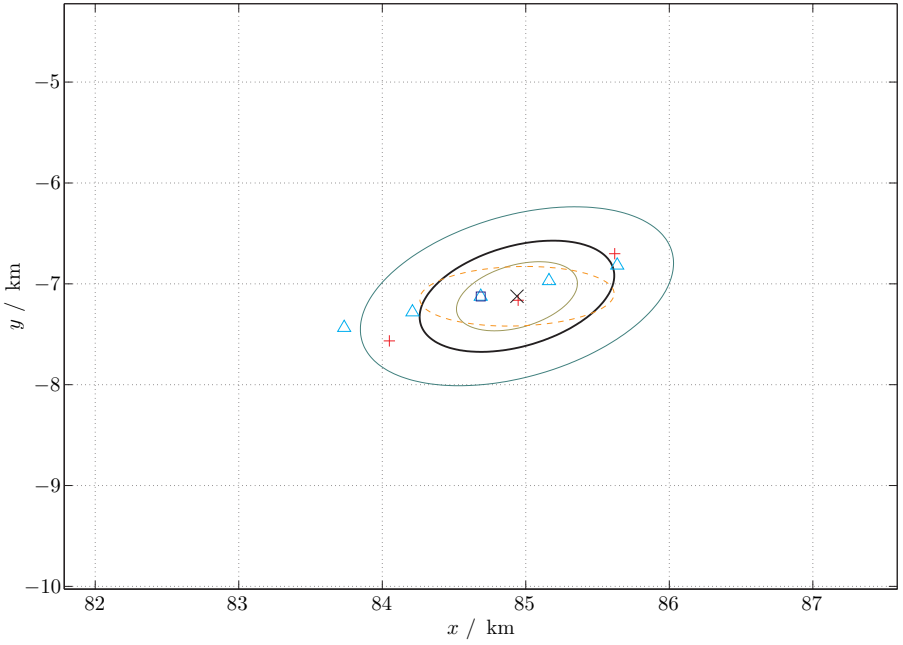

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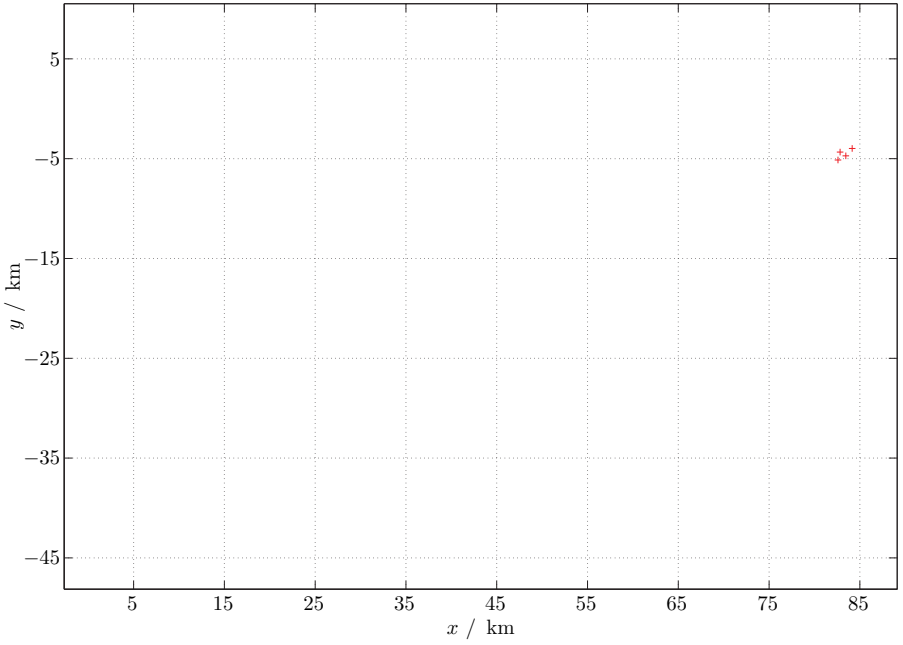

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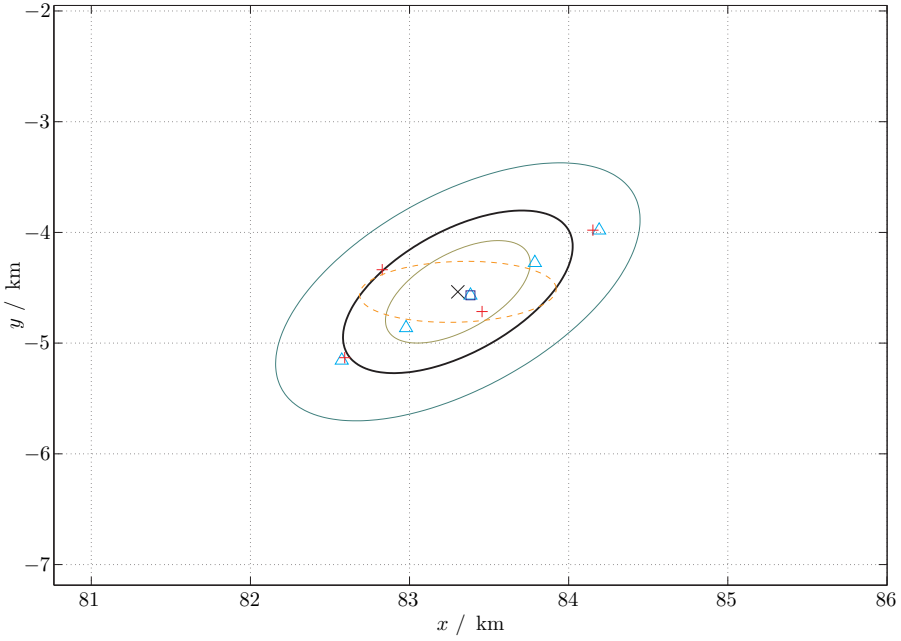

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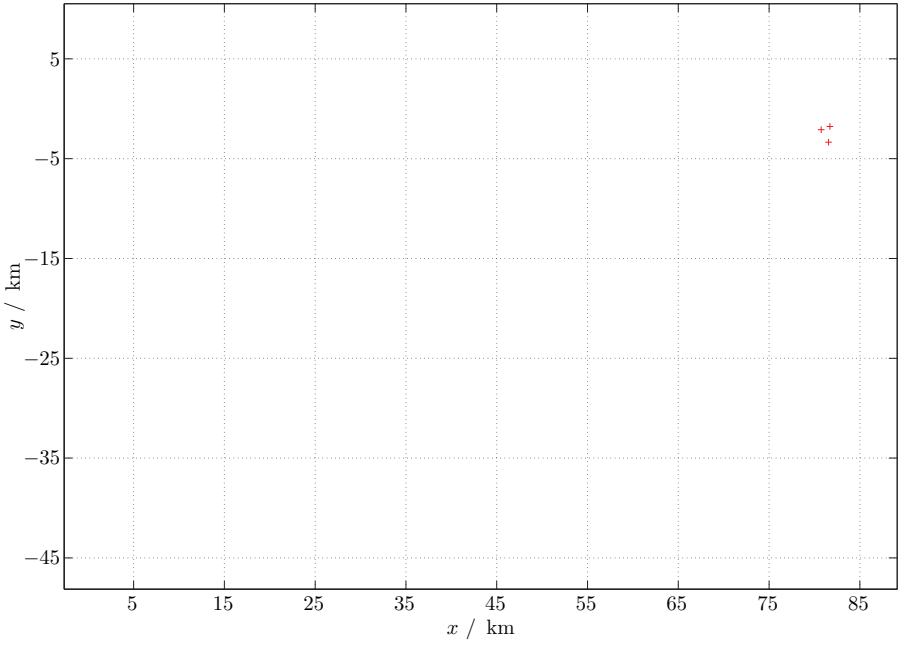

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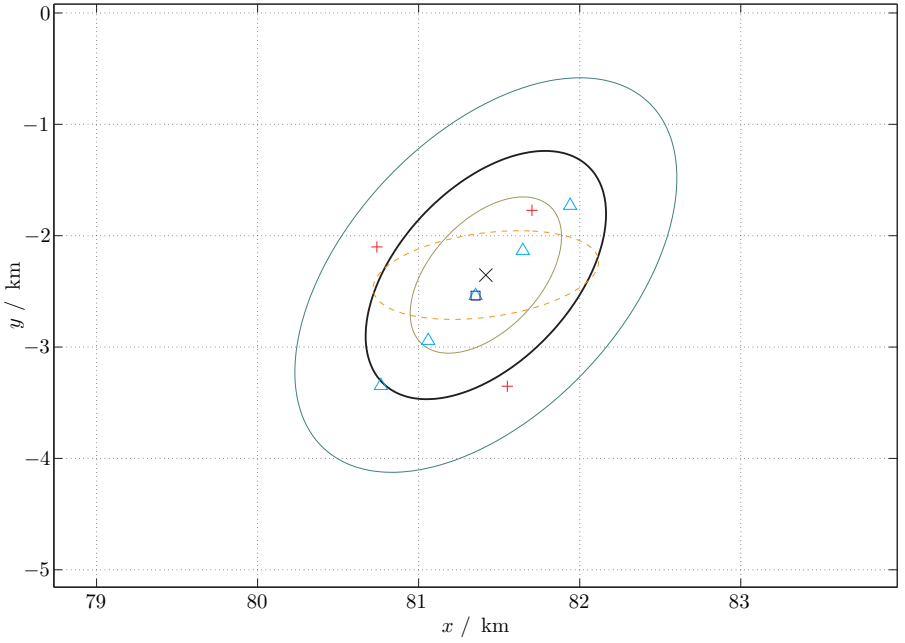

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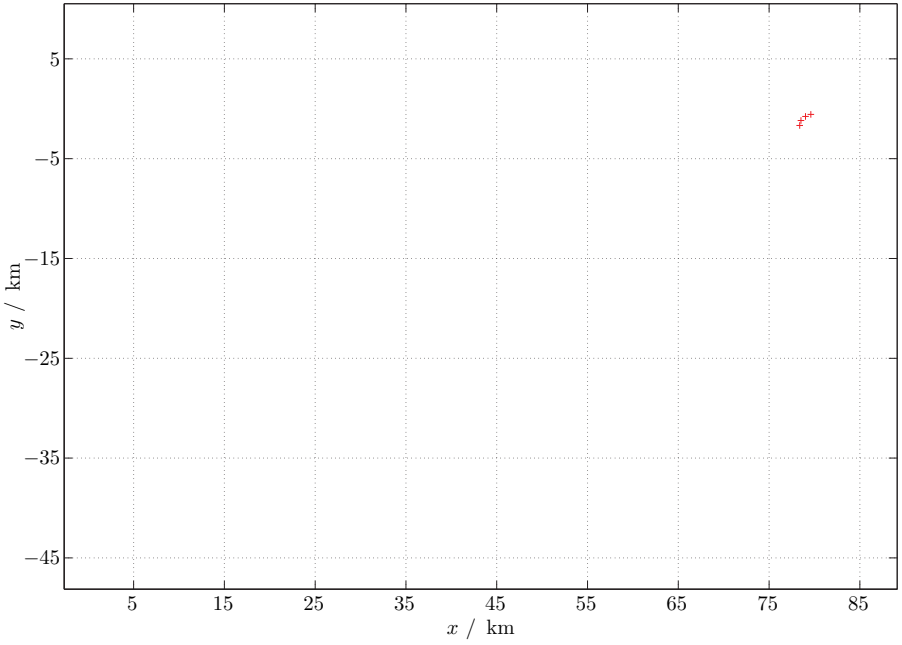

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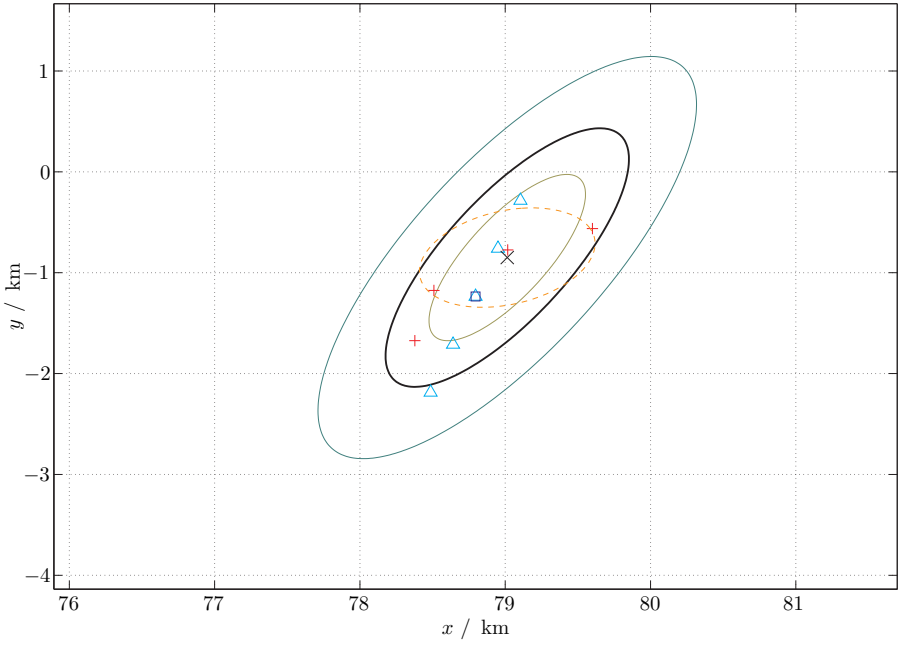

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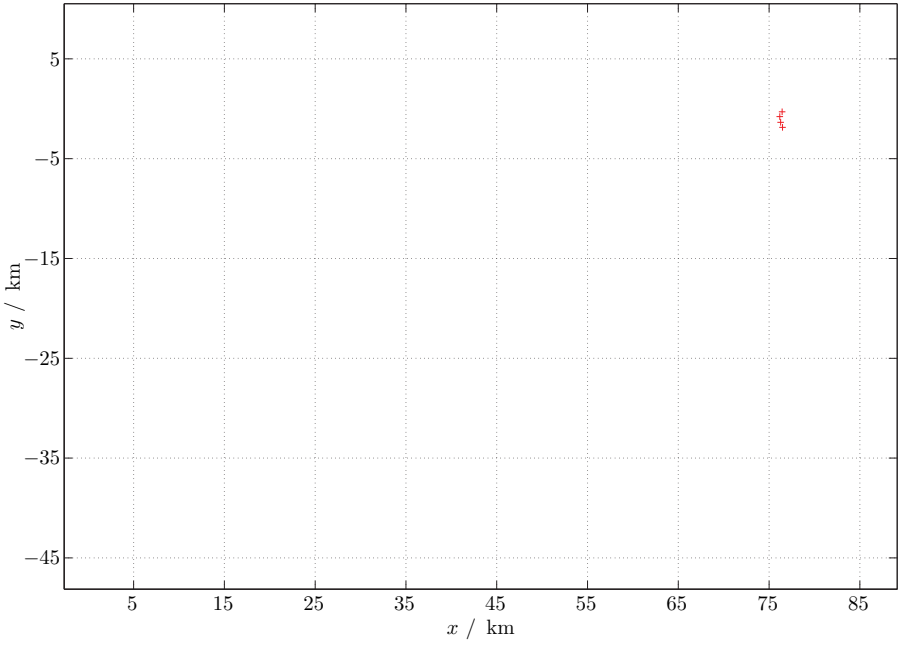

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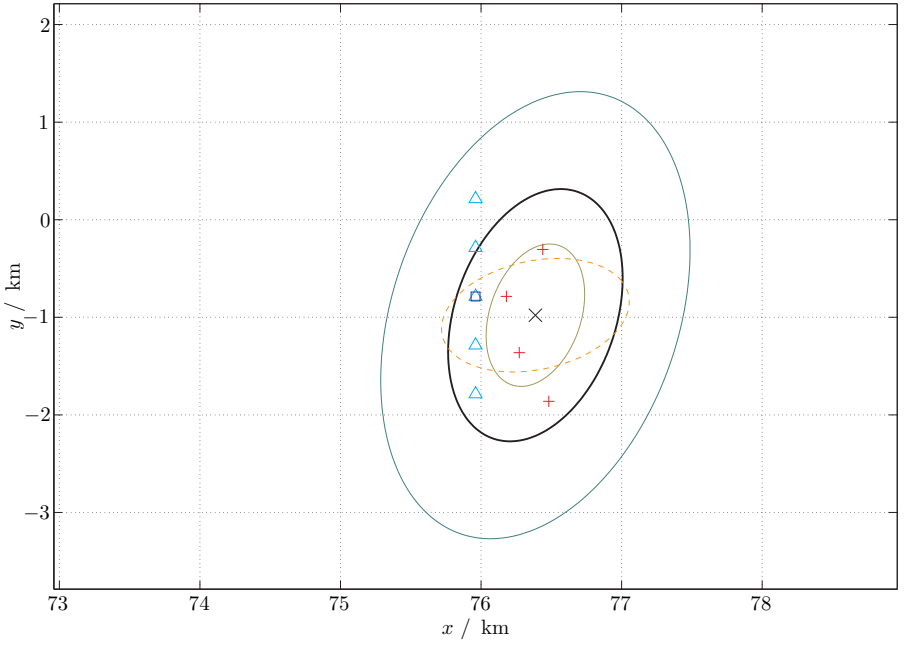

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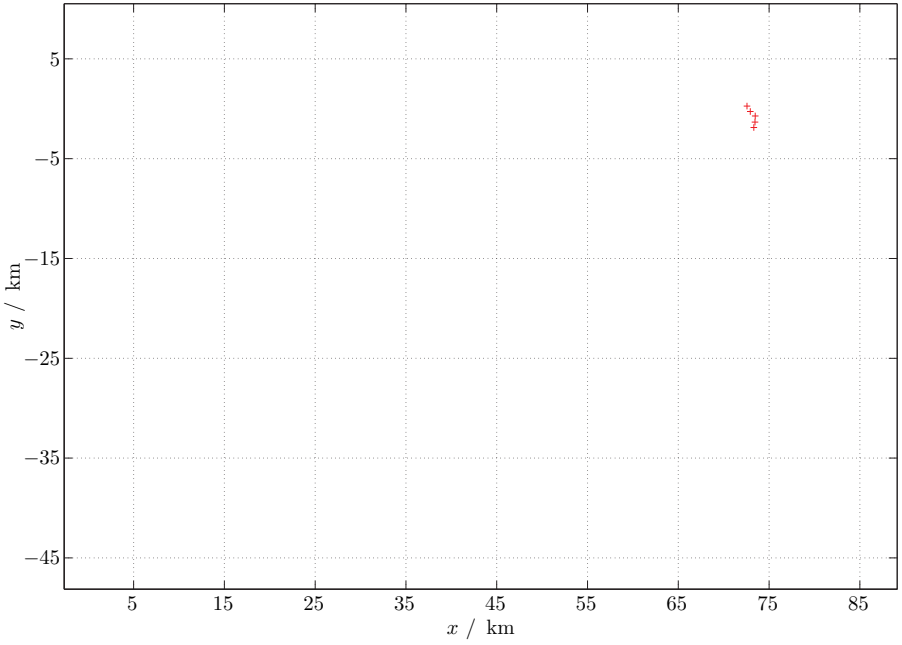

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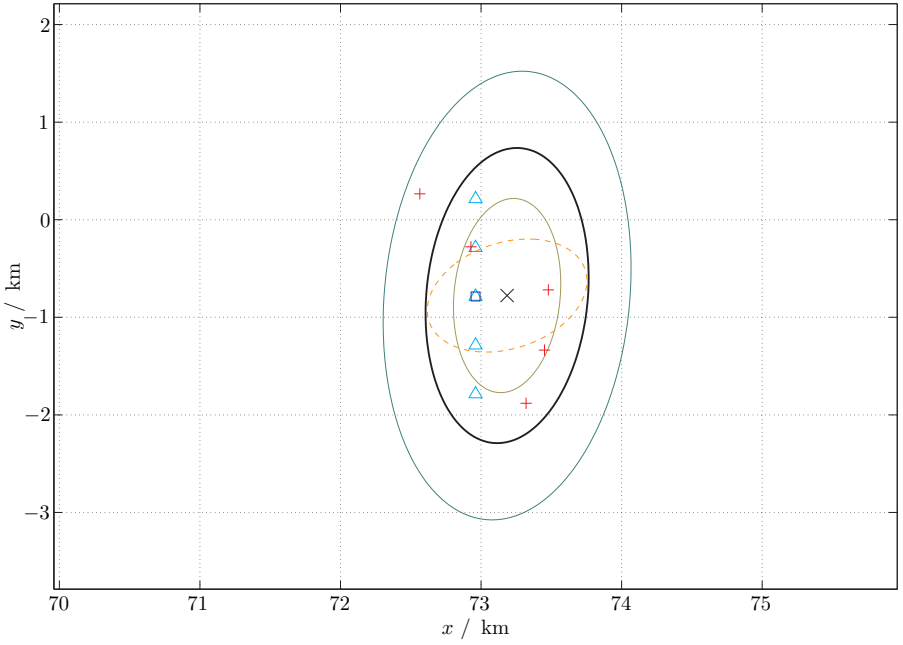

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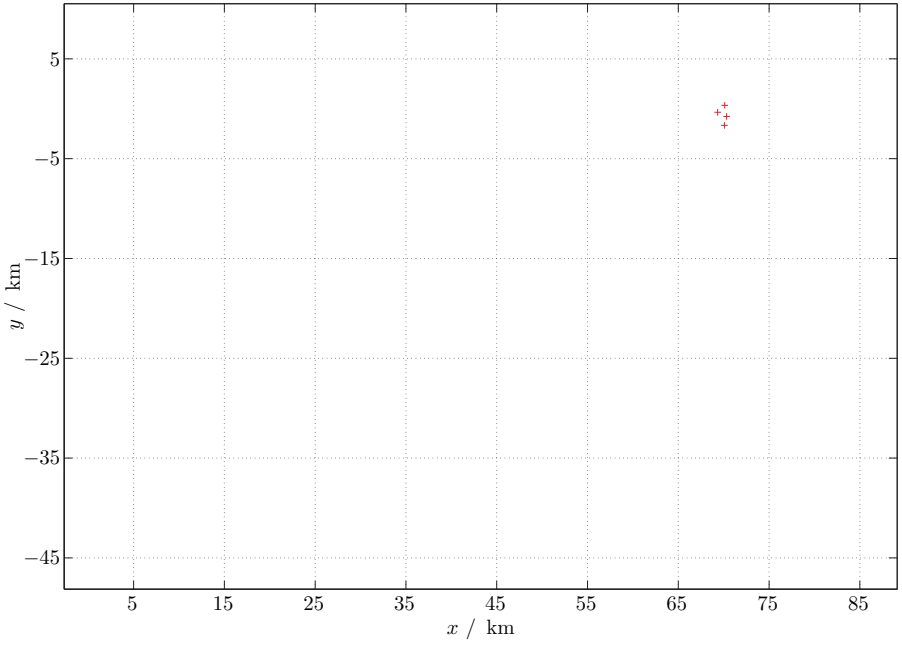

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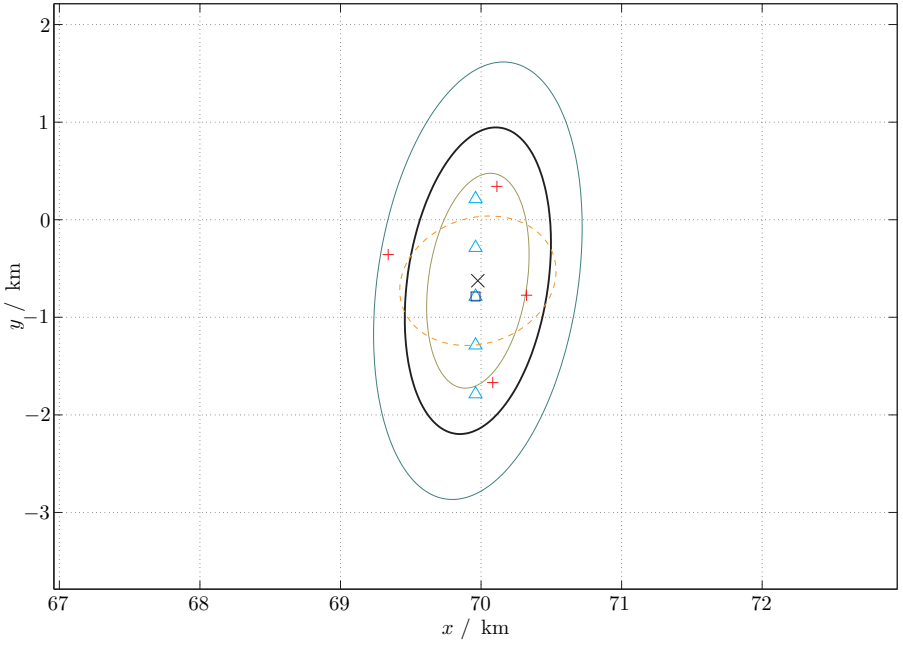

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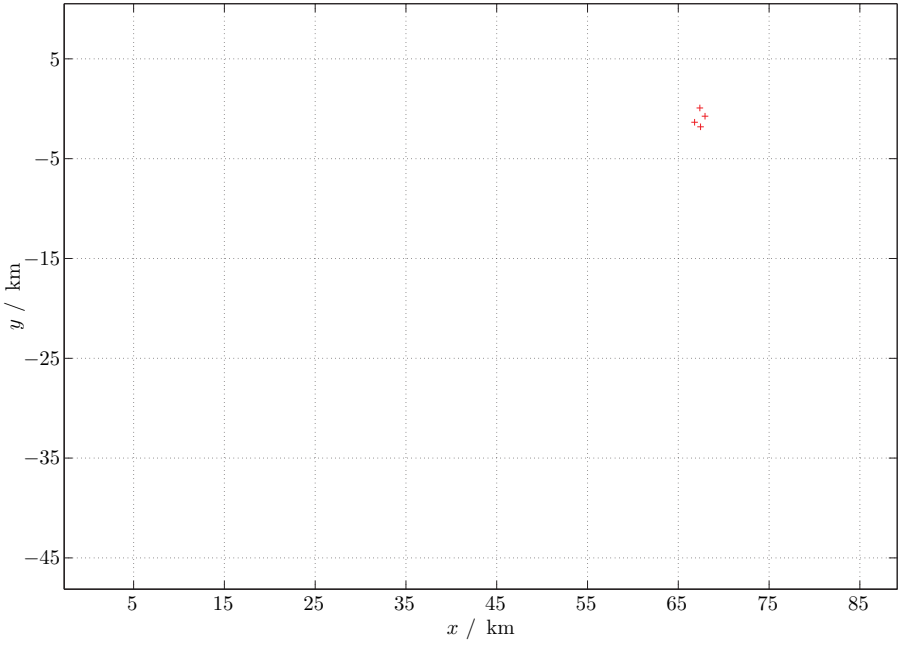

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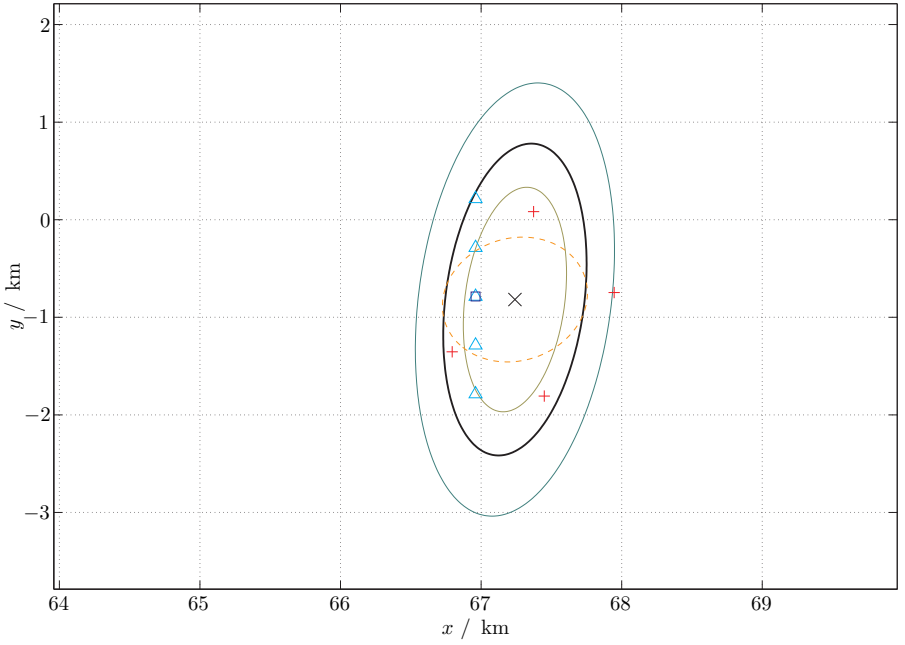

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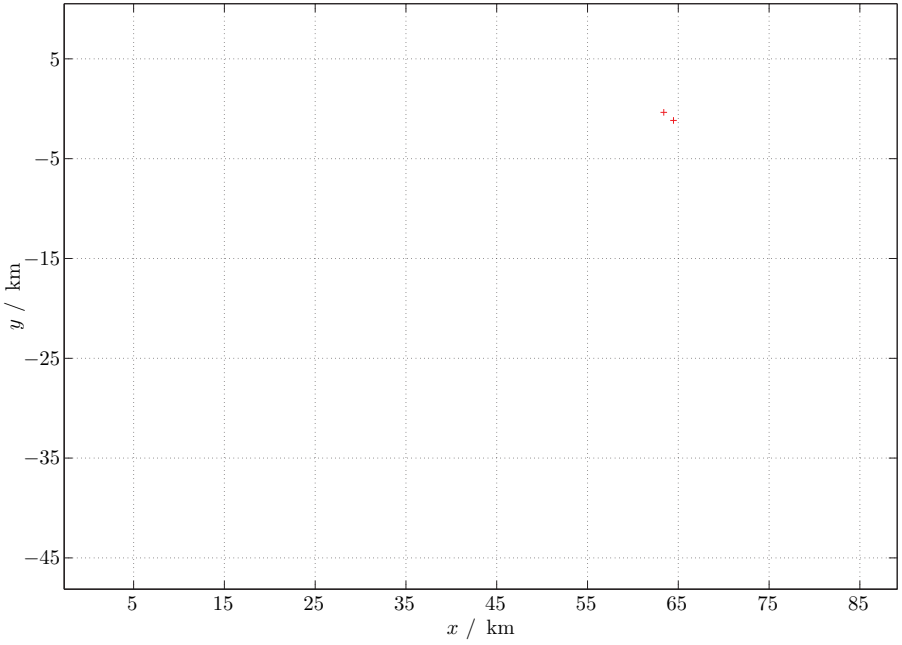

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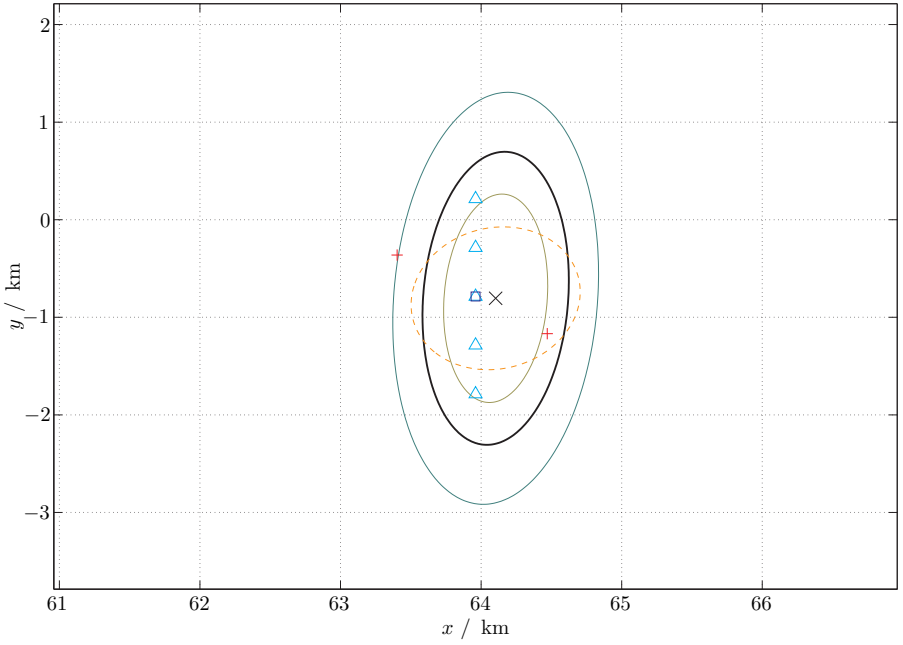

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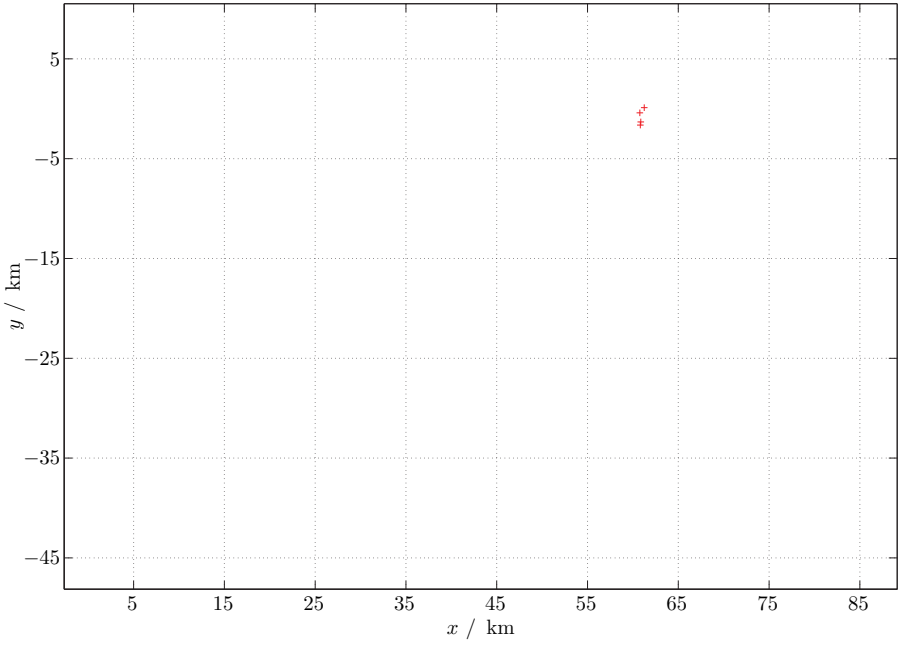

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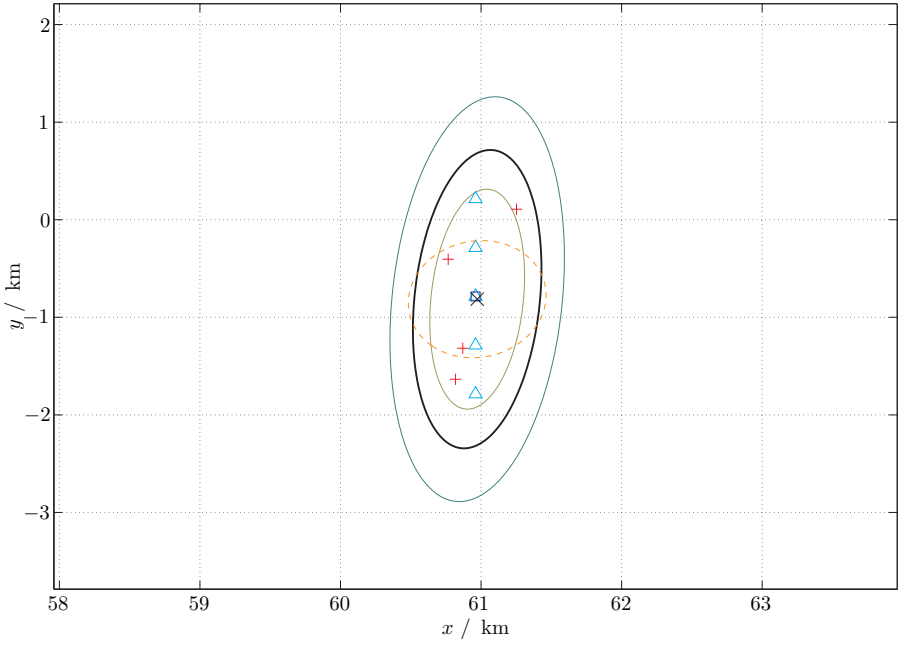

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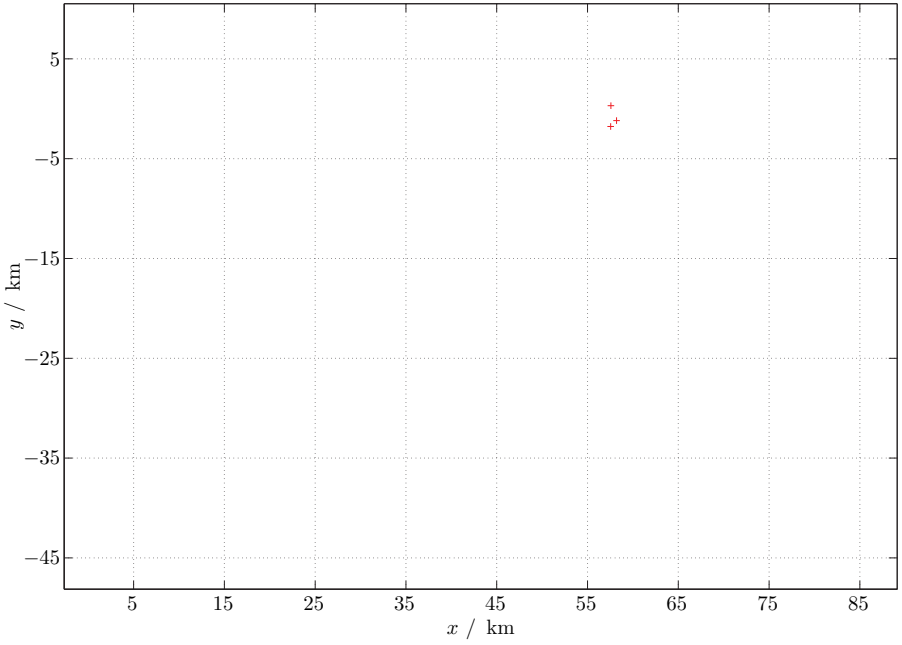

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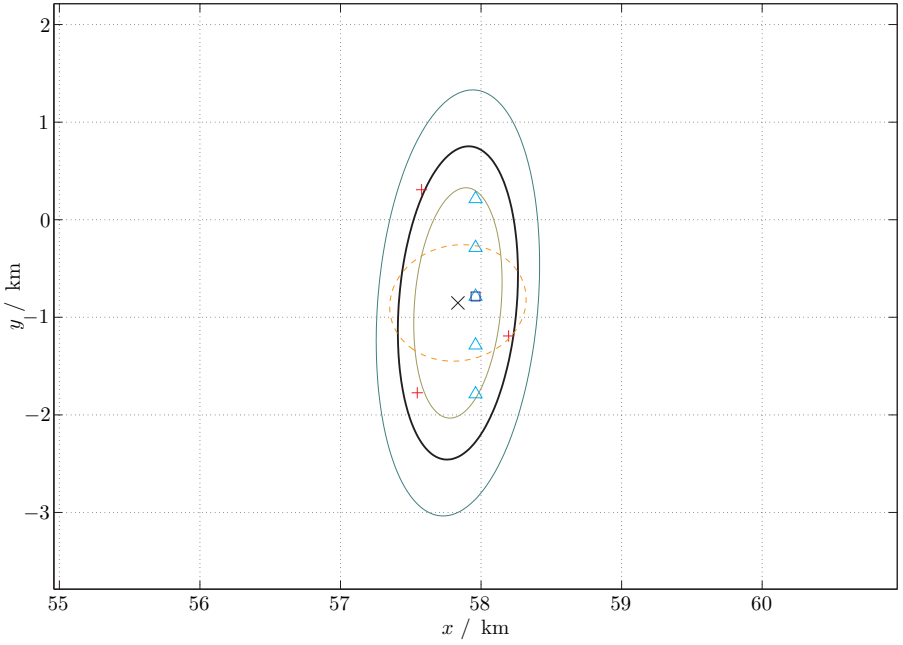

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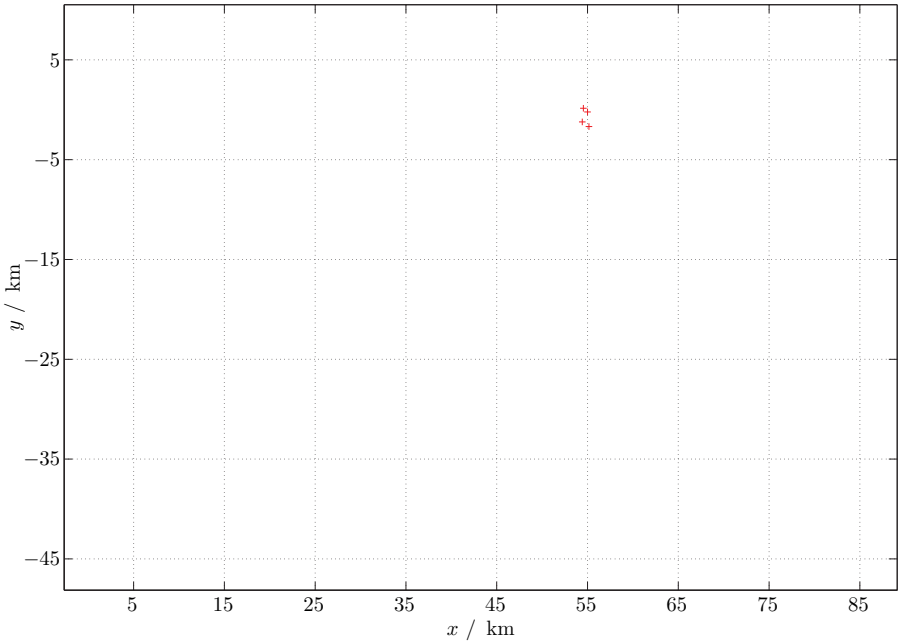

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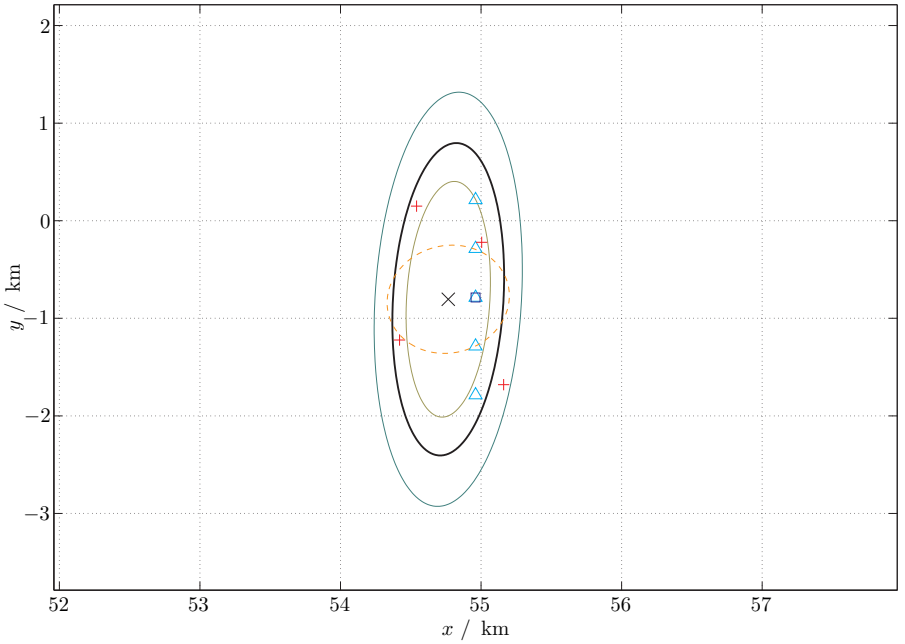

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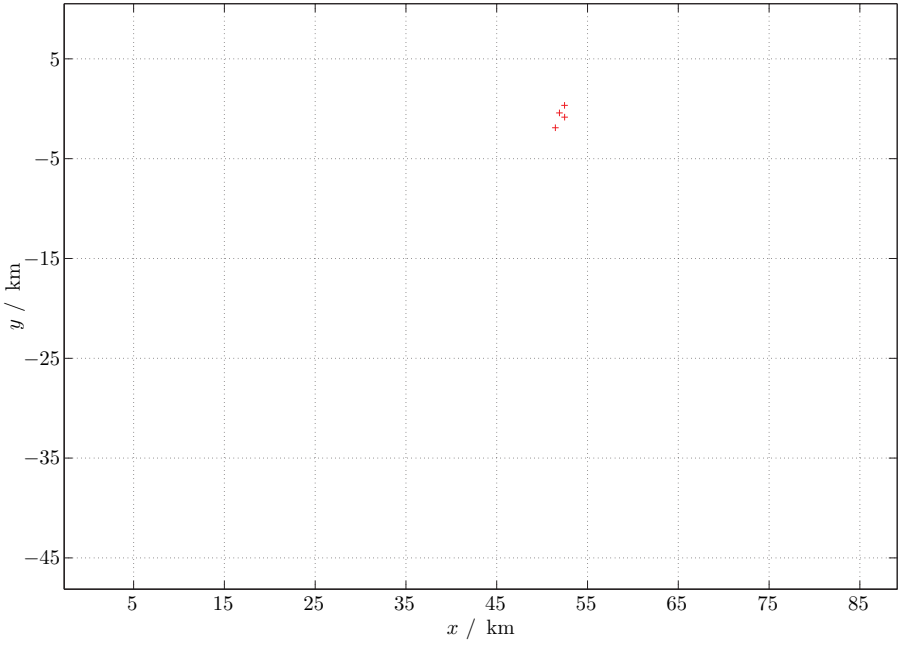

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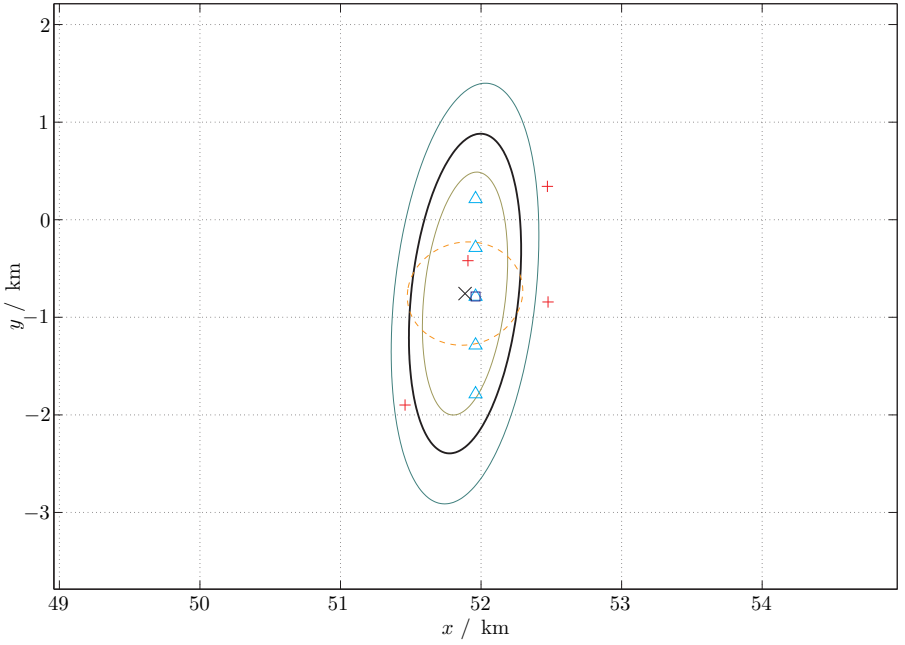

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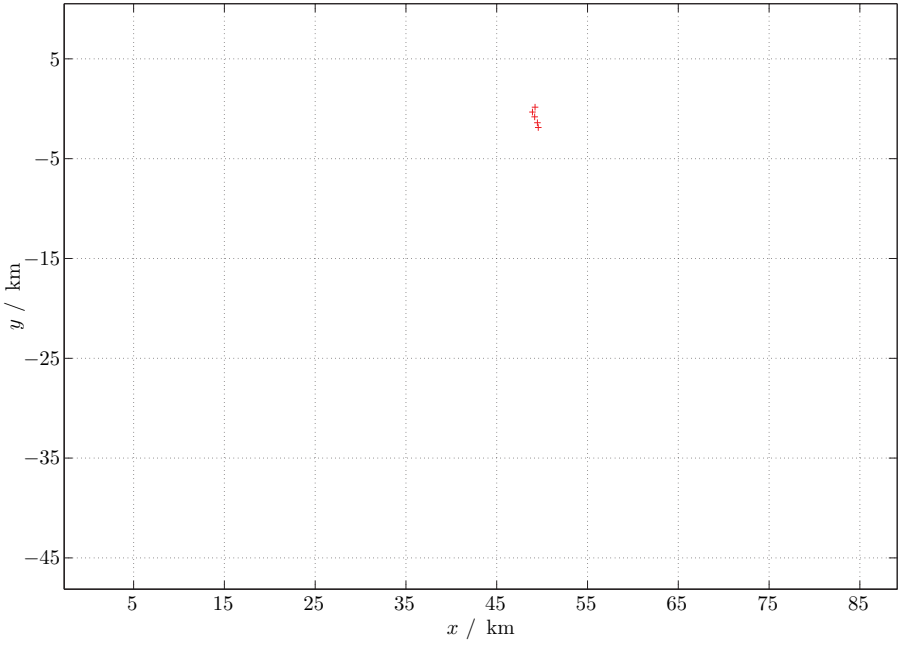

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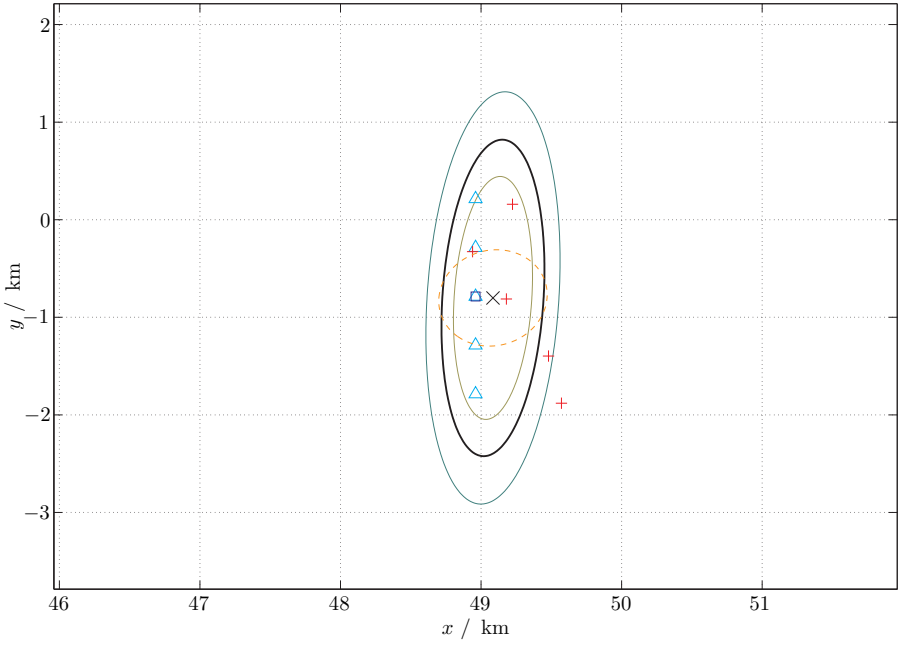

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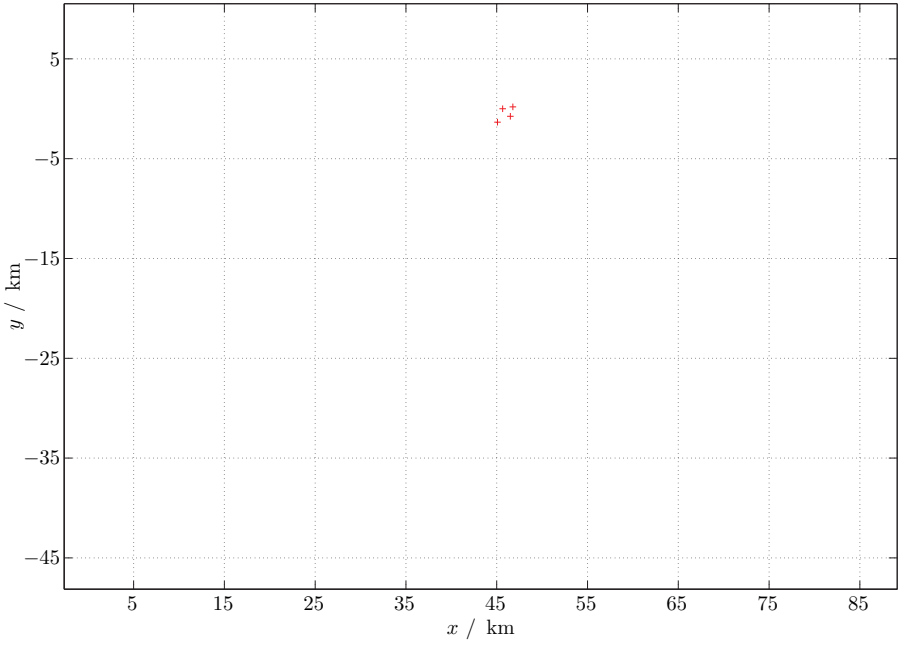

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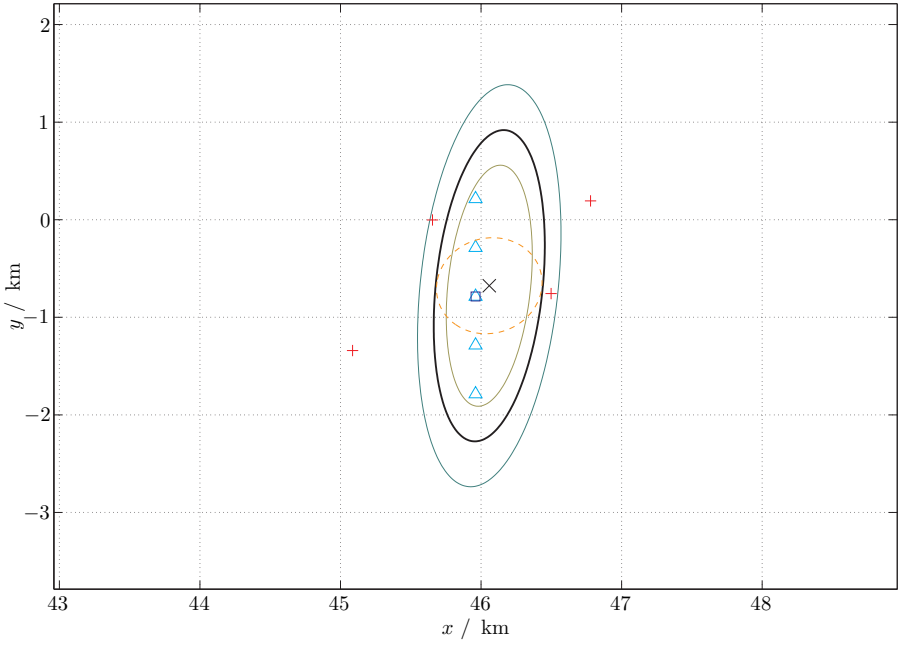

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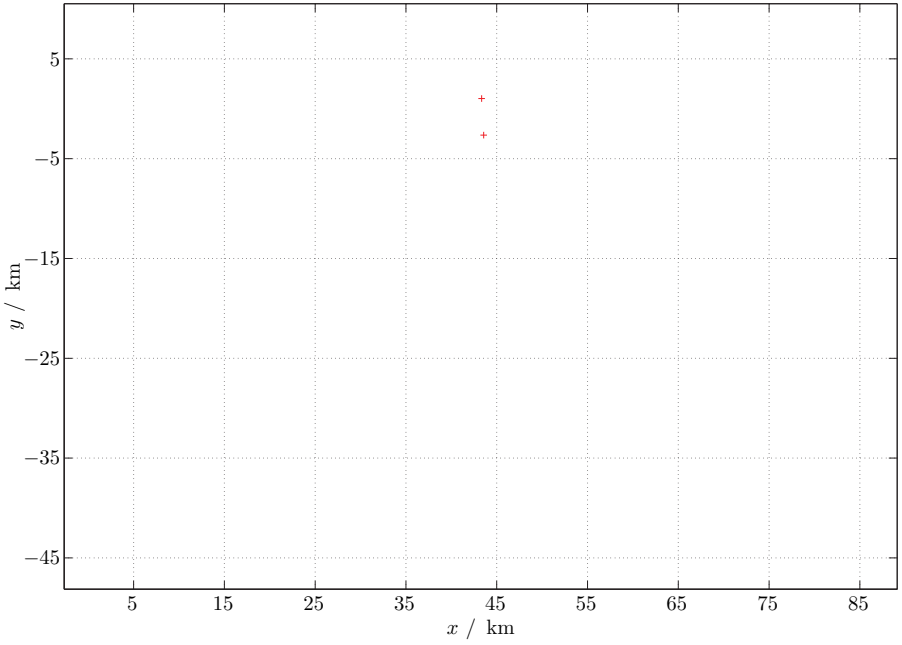

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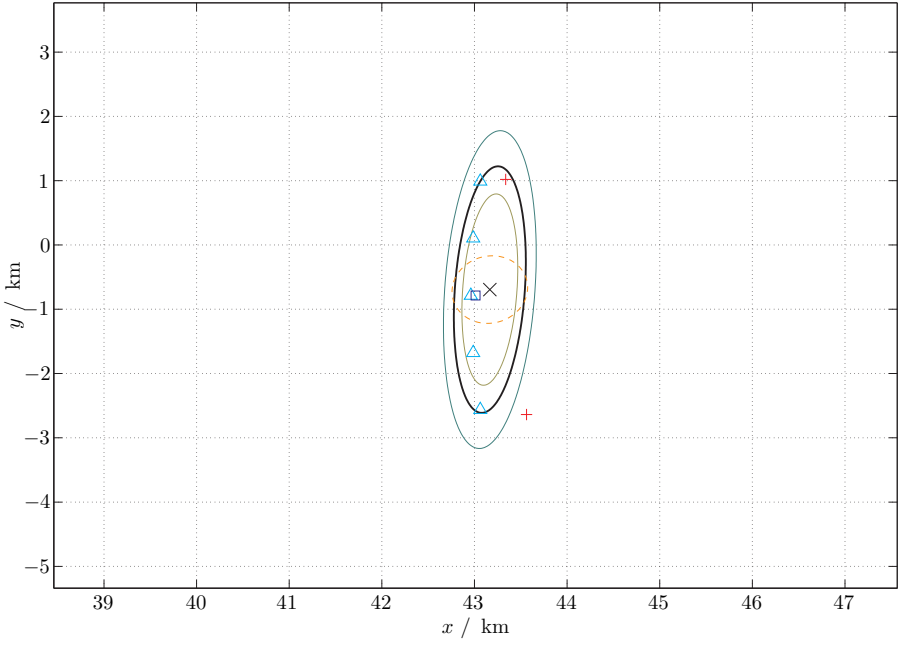

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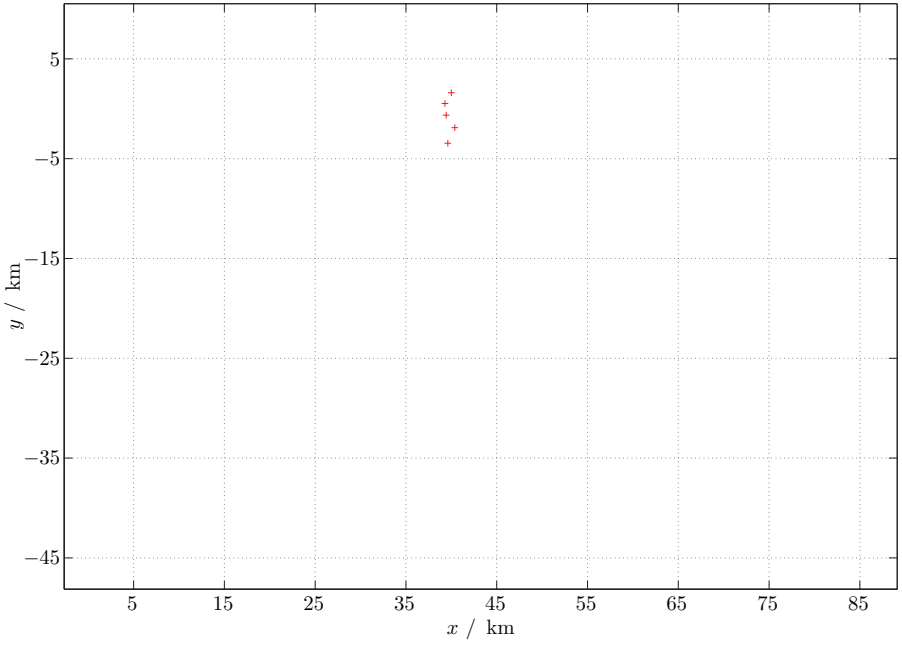

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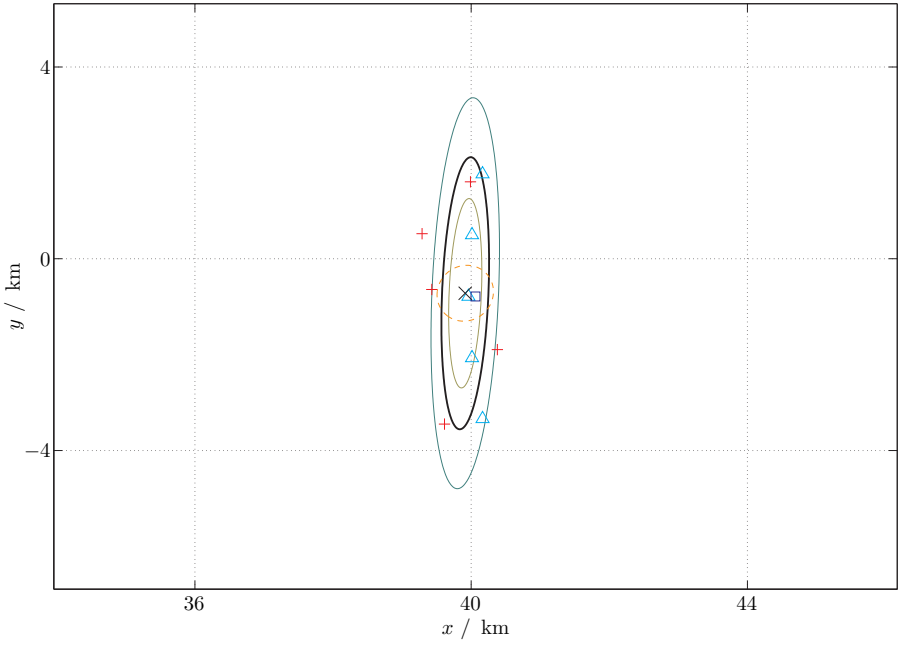

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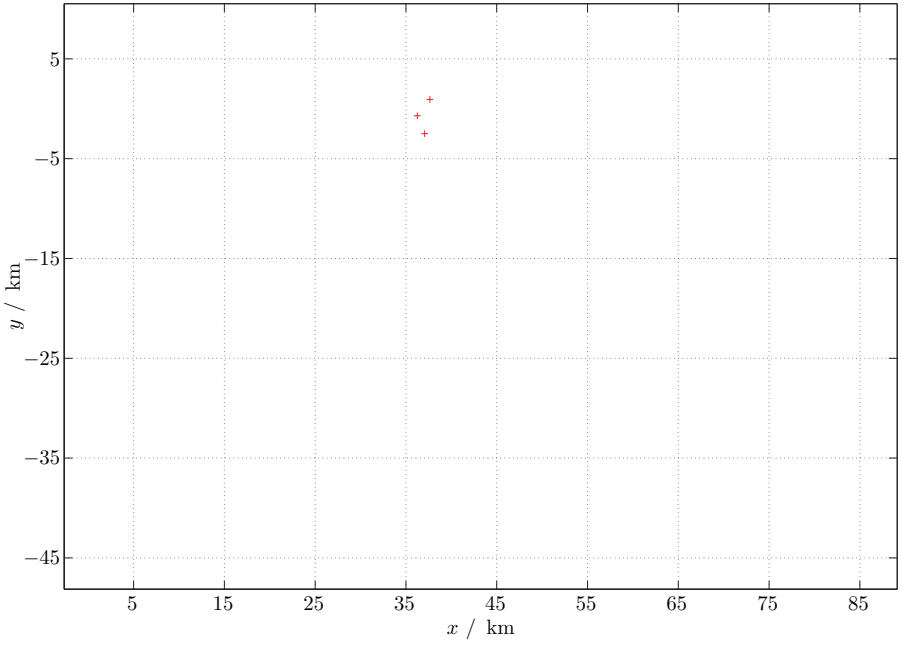

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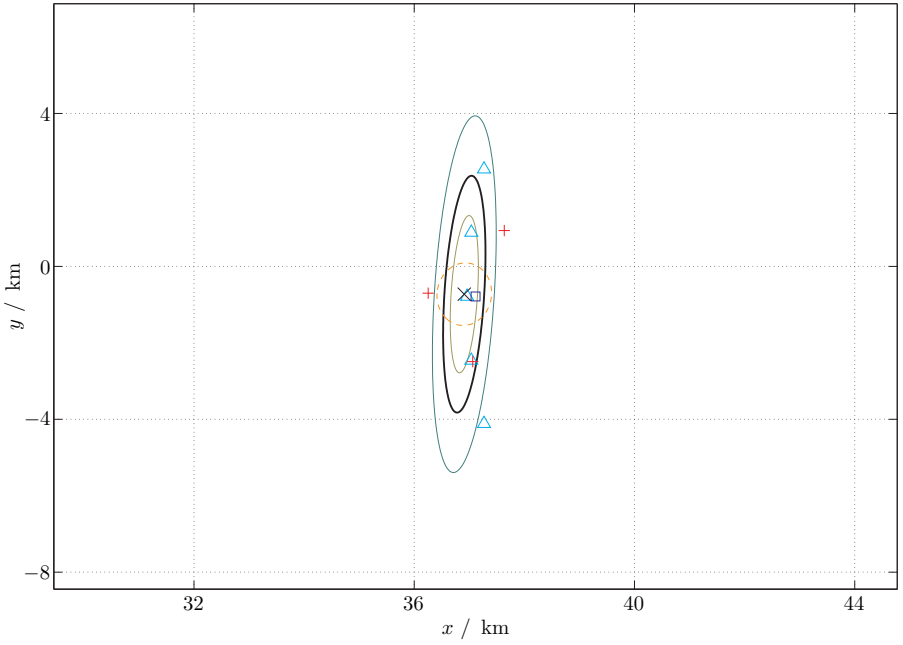

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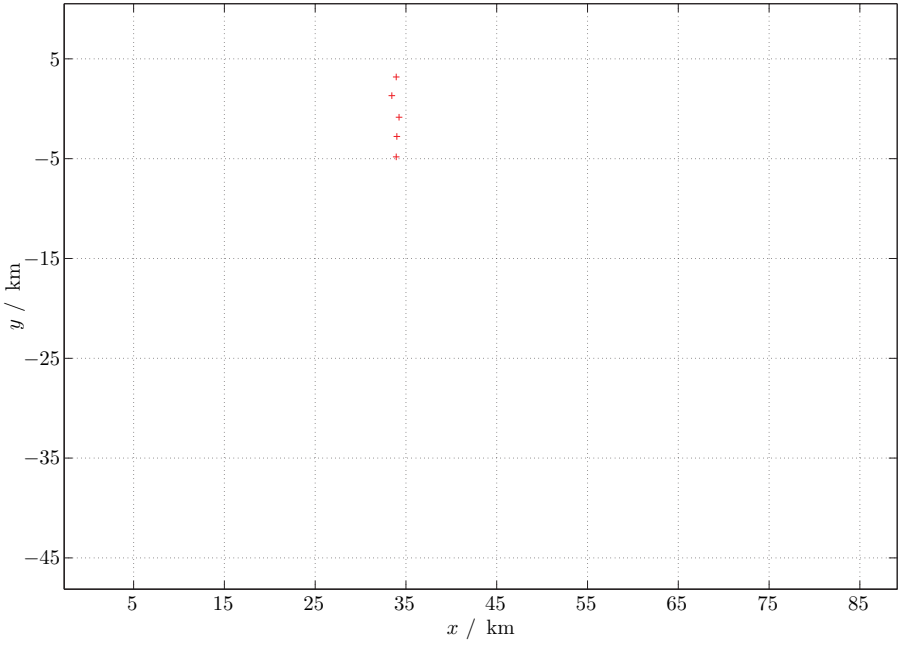

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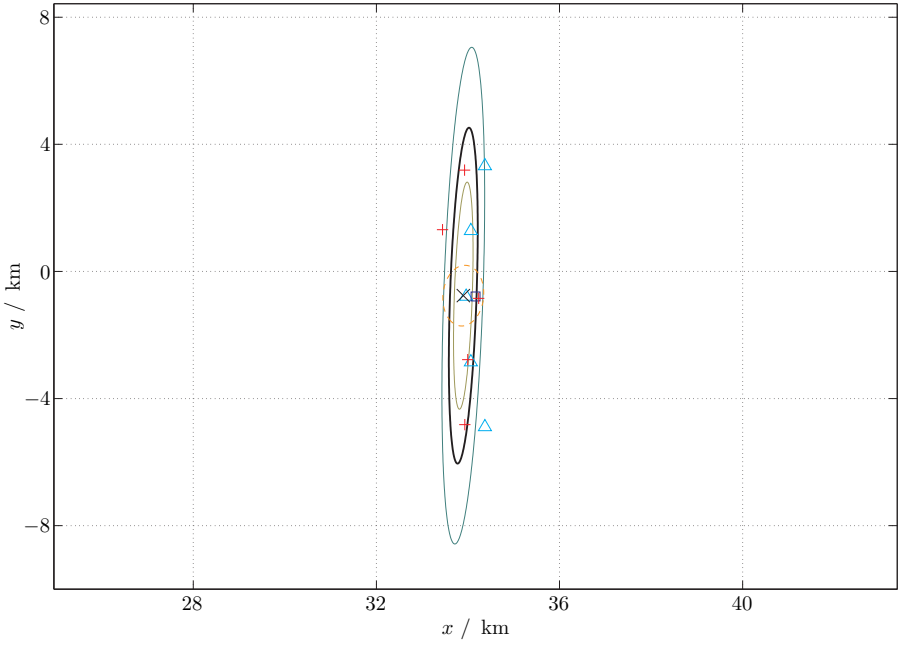

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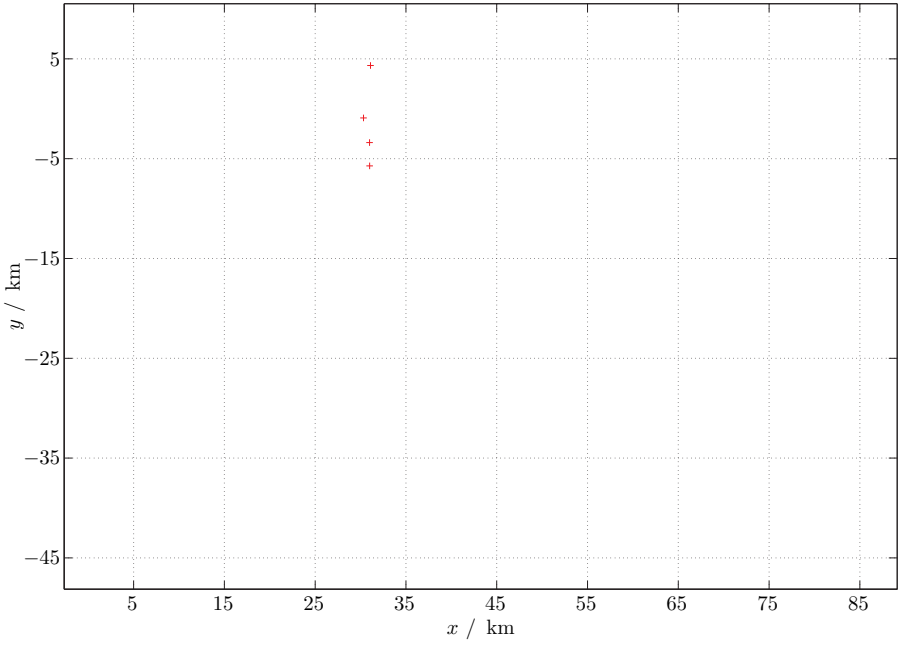

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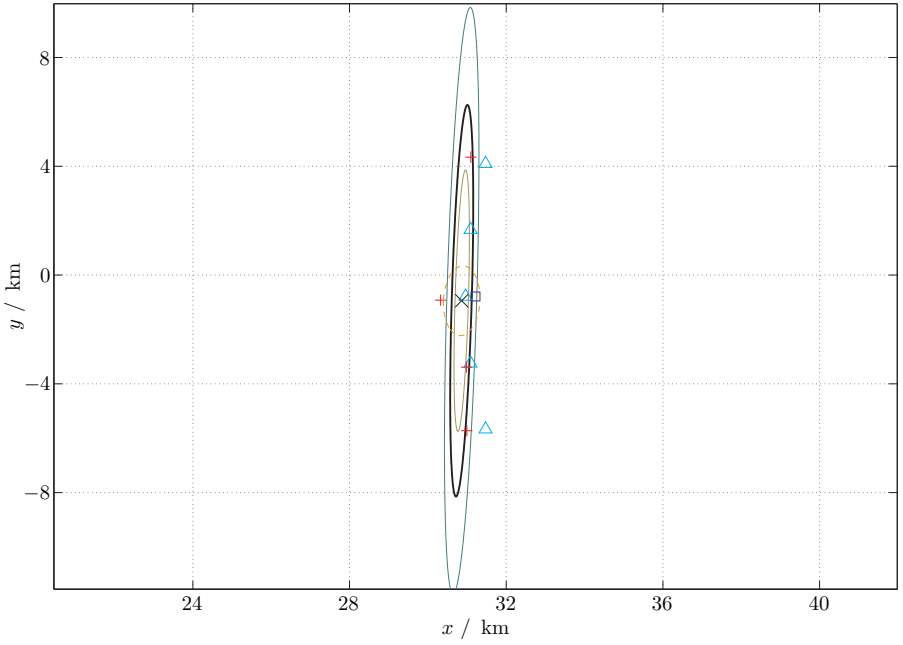

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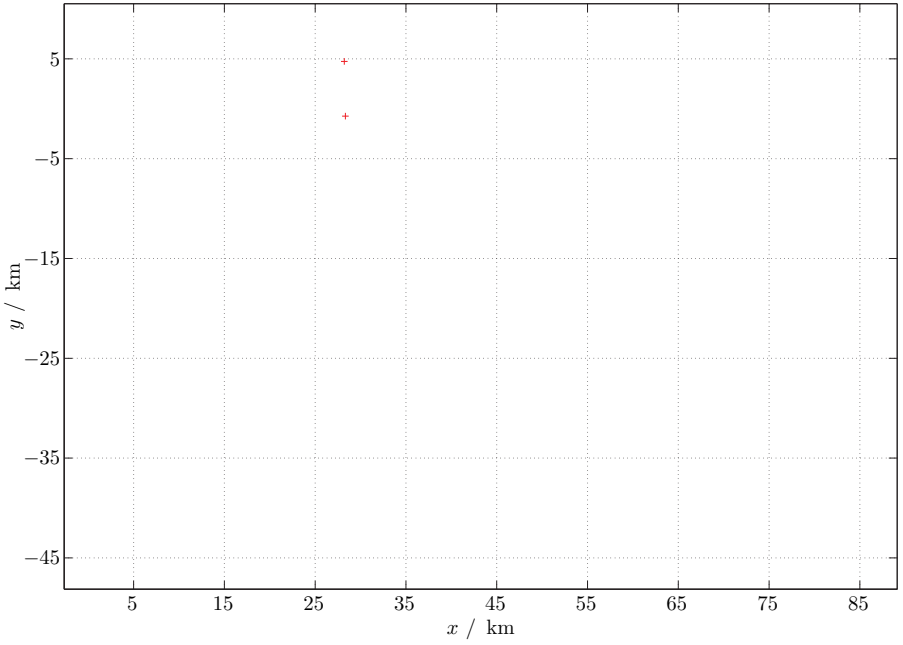

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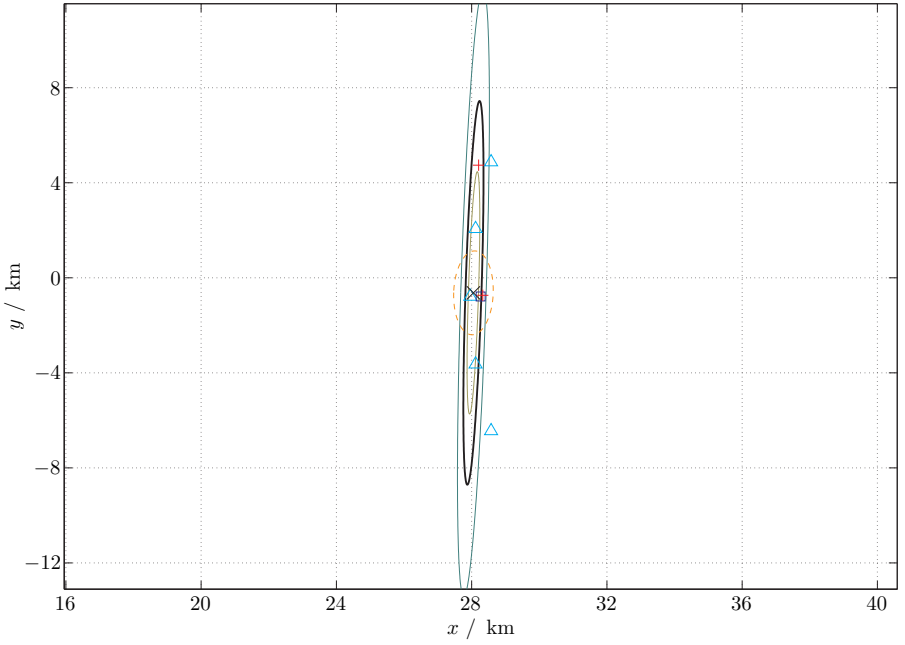

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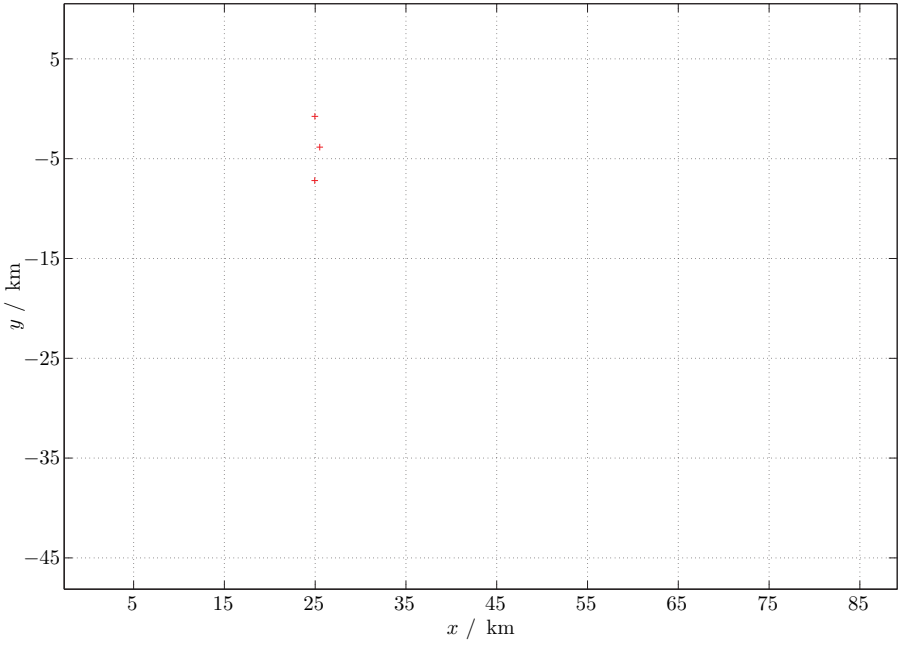

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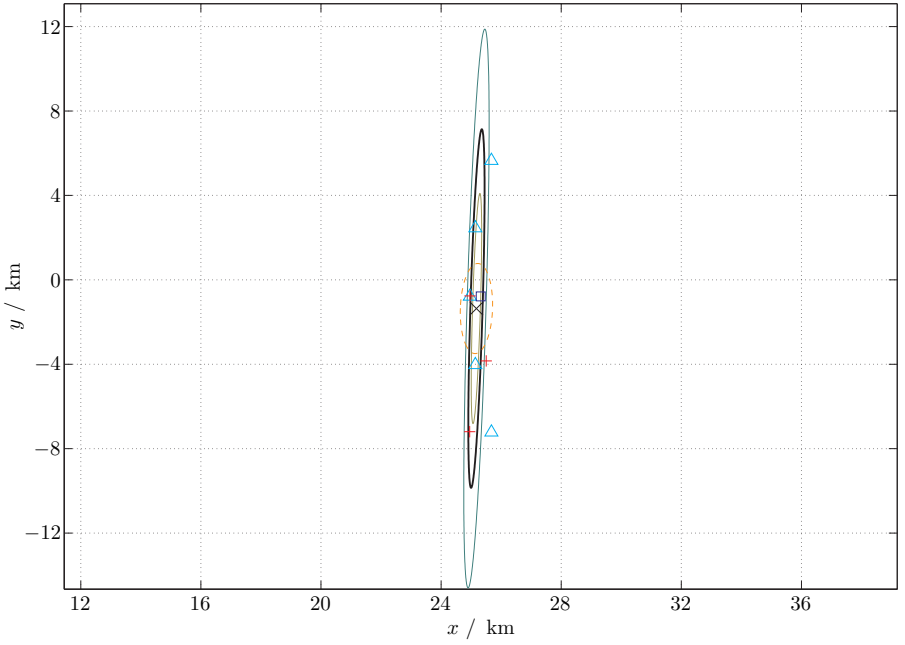

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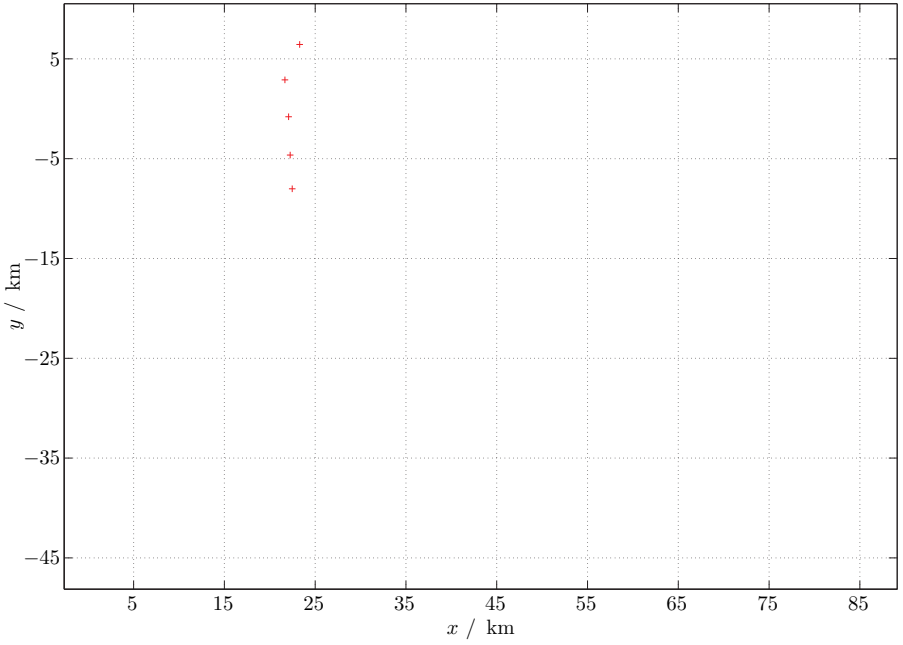

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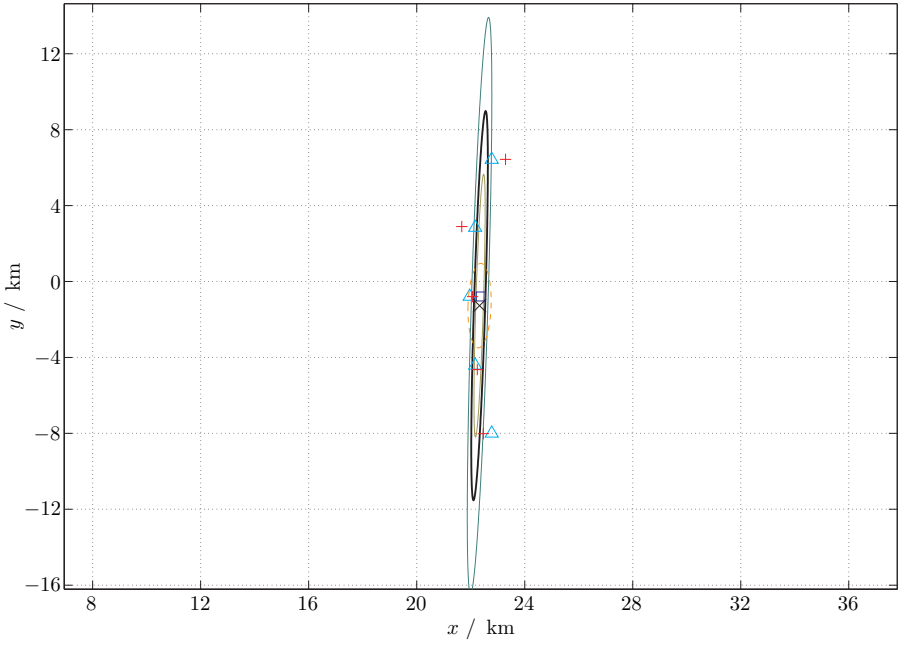

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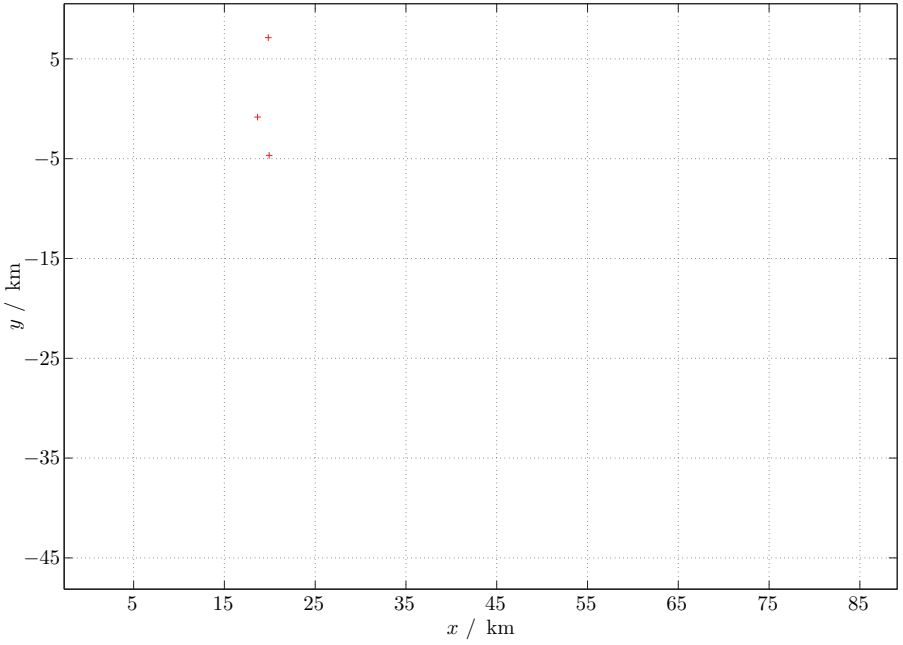

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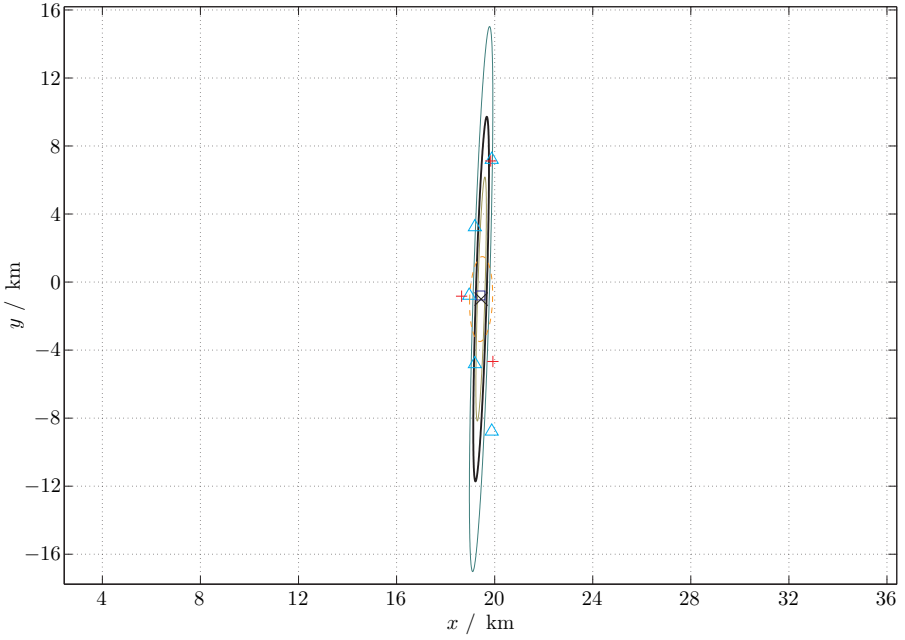

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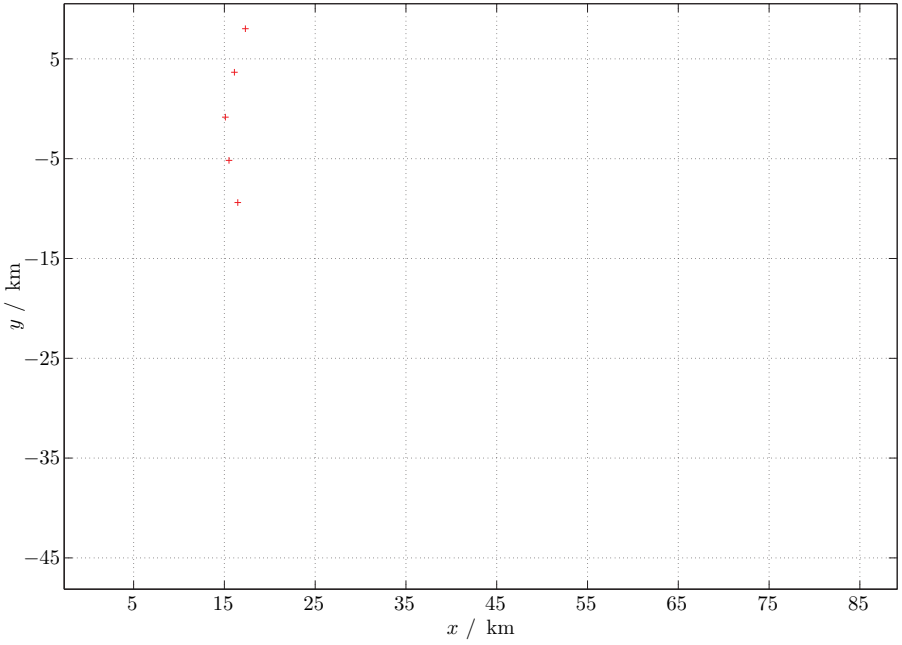

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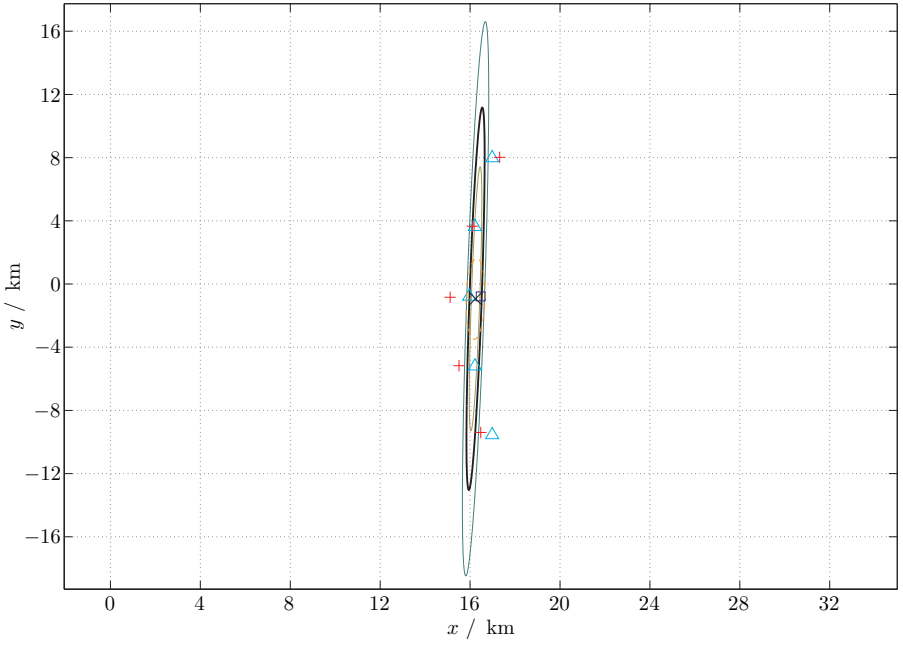

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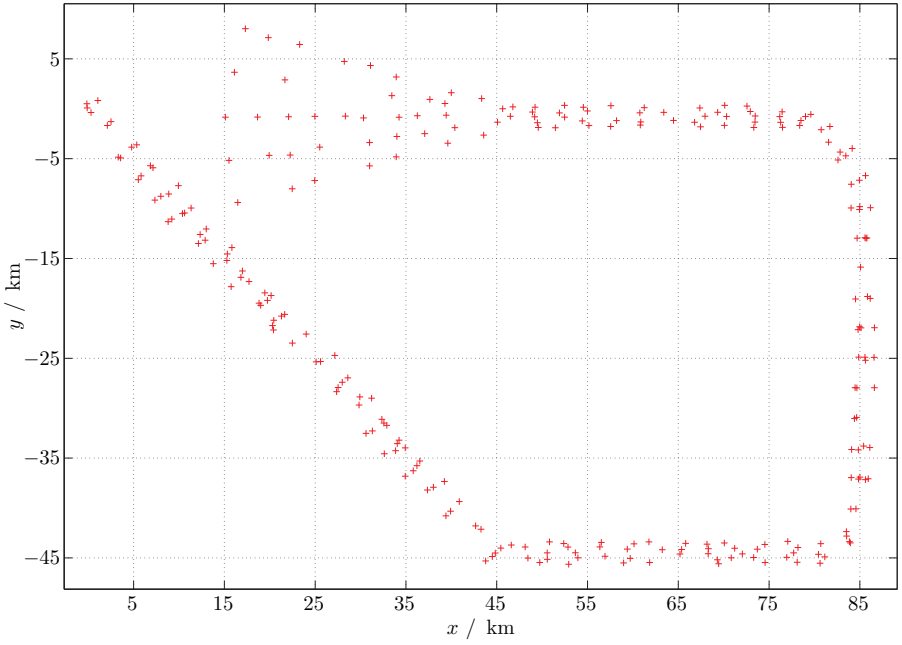

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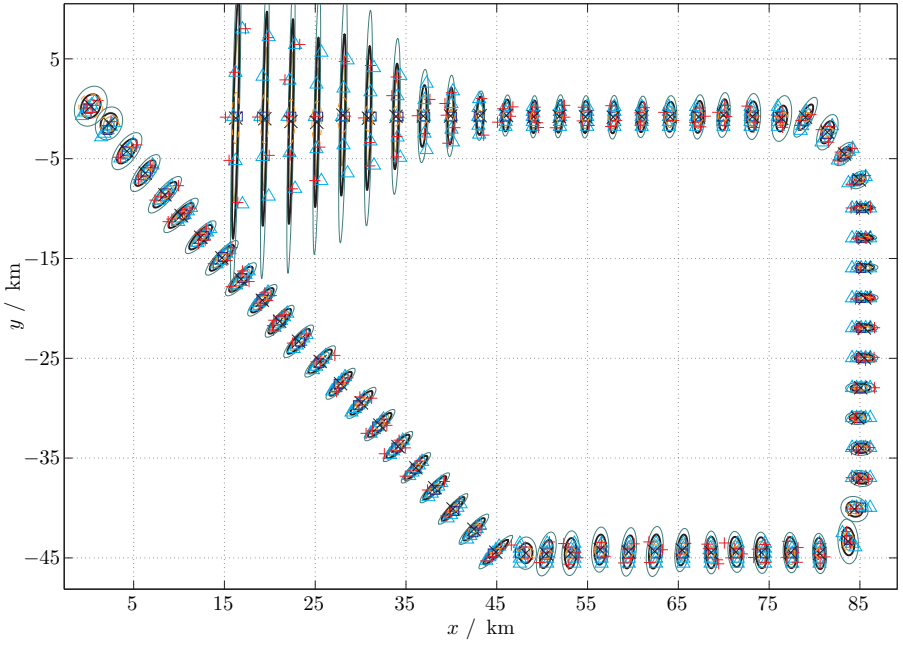


- **Basic Work:**

  – Koch, W., *Bayesian Approach to Extended Object and Cluster Tracking using Random Matrices.* In: IEEE T-AES, Vol. 44, No. 3, p. 1042-1059, 2008.

- **Embedding into Multiple Object Tracking**

  – Wieneke, M., Koch, W., *Probabilistic tracking of multiple extended targets using random matrices.* In: Proc. SPIE, Vol. 7698, (2010); extended version under review IEEE T-AES.

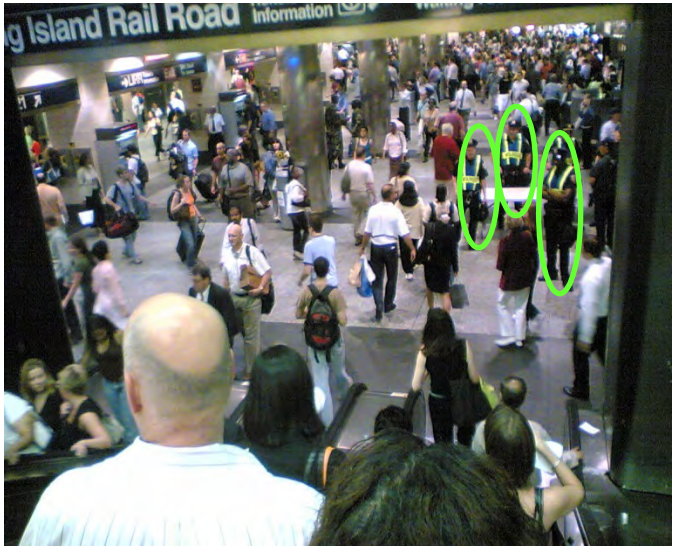
- **Integration of Context Information, Robustness**

  – Koch, W., Feldmann, M., *Cluster Tracking under Kinematical Constraints using Random Matrices.* In: Robotics and Autonomous Systems, vol. 57, no. 3, pp. 296–309, 2009.

  – Feldmann, M., Fränken, D., Koch, W., *Robust Tracking of Extended Objects and Group Targets using Randon Matrices.* Under review for: IEEE T-SP.

1. Aspects of Tracking-derived Anomaly Detection
2. Tracking of Extended Objects and Object Clusters
3. Looking at Emerging Security and Civilian Topics

Multiple Sensor Security Assistance Systems

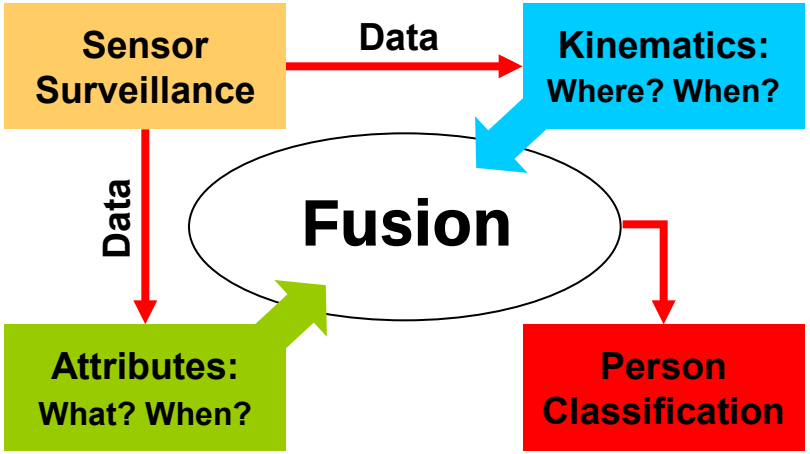


General Task

Covert & Automated Surveillance of a Person Stream: Identification of Anomalous Behavior

Towards a Solution

Exploit Heterogeneous Multiple Sensor Systems.



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Security Applications: Well-defined Access Regions.

Task: Detect persons carrying hazardous materials in a person flow.

Escalators / Stairways

Tunnels / Underground

Problem: limited spatio-temporal resolution of chemical sensors

Solution: compensate poor resolution by space-time data fusion

Track Extraction / Maintenance	Video Data	Attributes
Laser-Range-Scanner Sensors	Supporting Information	Chemical Sensors

EU Project HAMLeT: Hazardous Material Localization and Person Tracking

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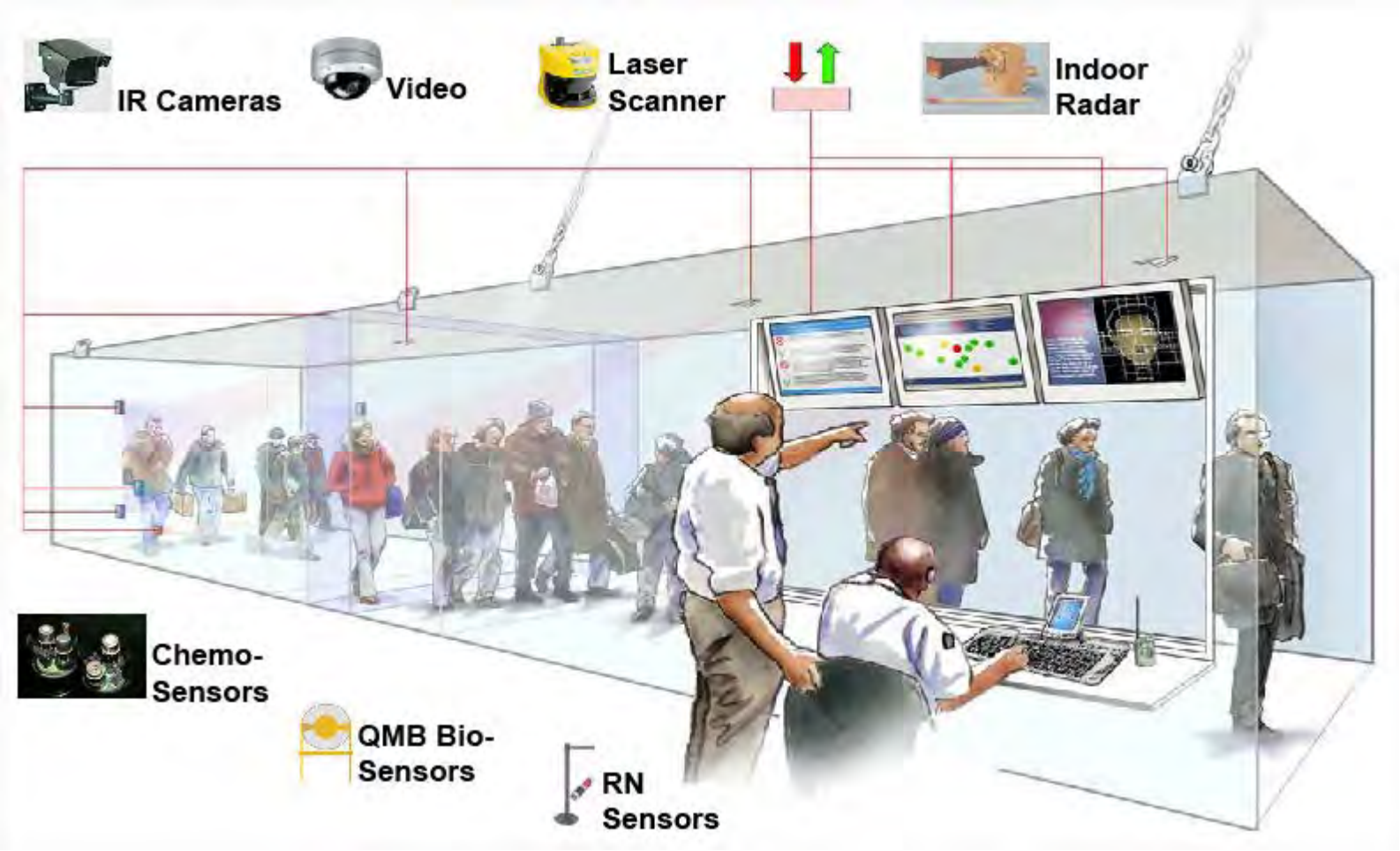
Security Applications: Well-defined Access Regions.

Task: Detect persons carrying hazardous materials in a person flow.



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Fusion: Kinematics Attributes

Given

Kinematic States of the observed Persons

$$\mathcal{X} = \mathcal{X}_{1:T} = \left\{ \{ \mathbf{x}_t^1, \ldots, \mathbf{x}_t^S \} \right\}_{t=1}^{T}$$

Attribute-Output $\mathbf{o}_t^{\mathsf{ch}}$ of the Chemo-Sensors, $\mathsf{ch} \in [1:5]$

$$\mathbf{o}_t^{\mathsf{ch}} \in \left\{ \bullet, \bullet, \bullet, \bullet, \bullet \right\} \qquad t \in [1:T]$$

Wanted

Classification Matrix $\mathsf{C} \in [0,1]^{5 \times S}$

	1	2	3
No Alert			
Alert I			
Alert II			
Alert III			
Alert IV			

Persons

Alert Levels

Probability that Person 3 has Attribute

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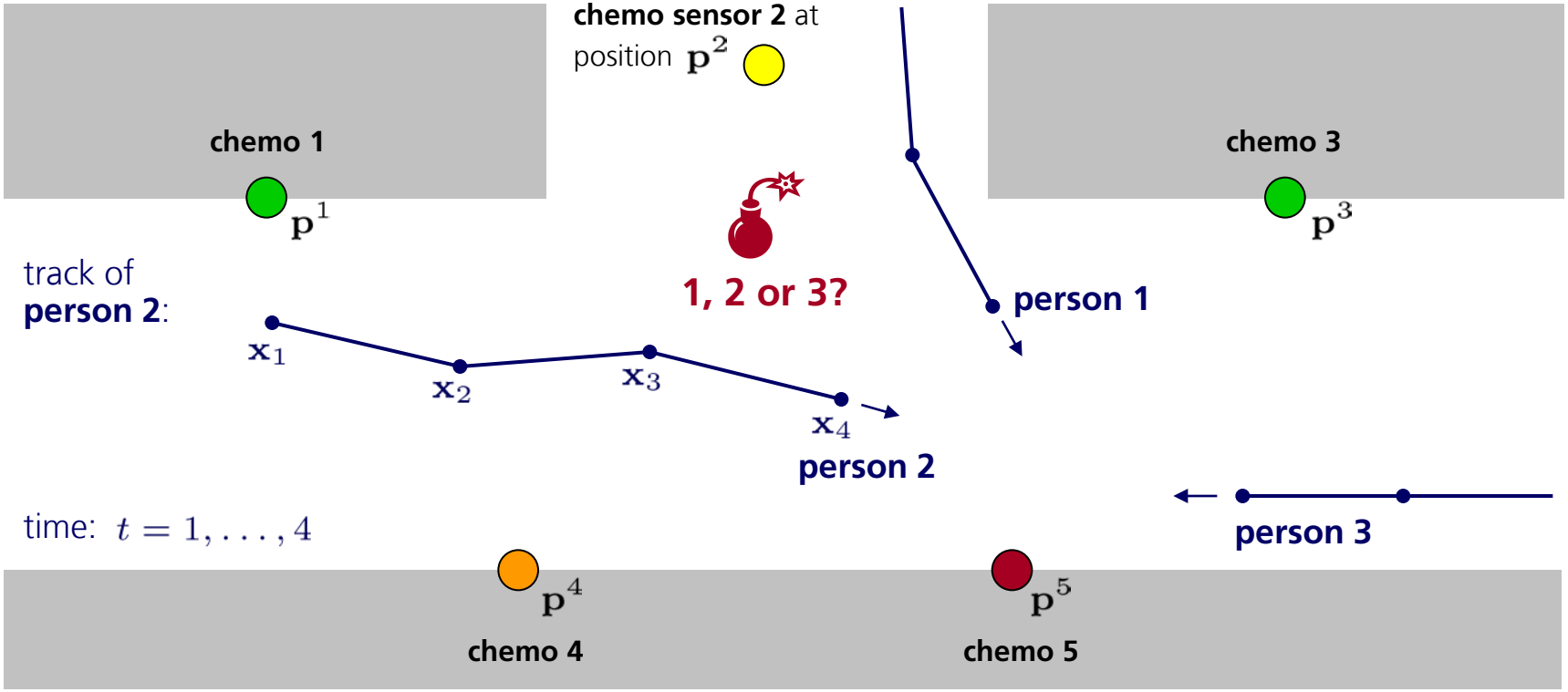
Classification problem: Why carries the bomb?

Fuse all position and signature measurements over time!

Position measurements: reconstruction of the kinematic behaviour

CBRNE signatures: low space-time resolution → non-trivial association



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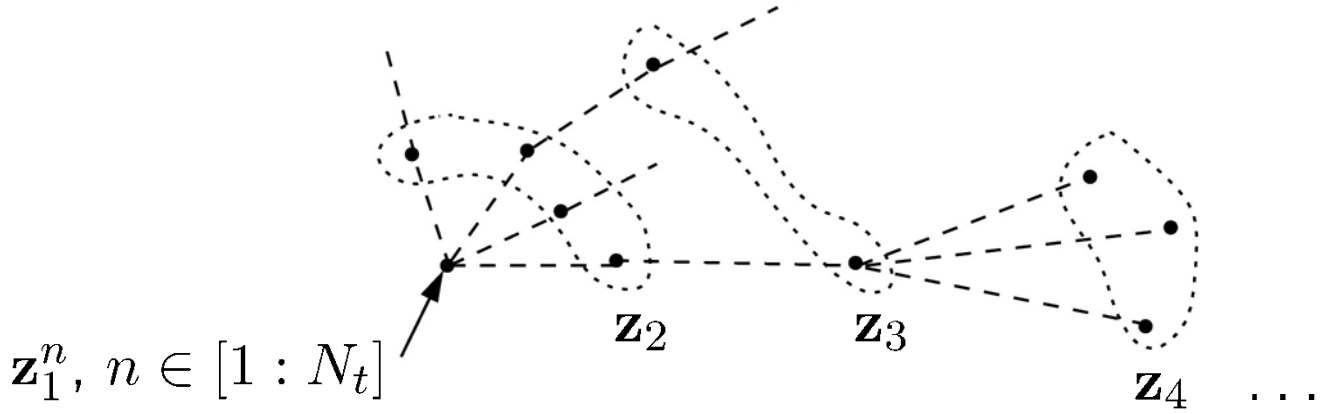
Multiple Person Tracking

Association Problem

Multitude of possible Interpretations

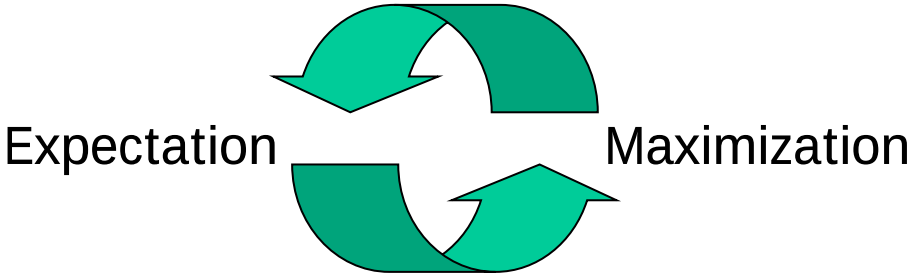


Solution

Probabilistic Multiple Hypotheses Tracking (PMHT)

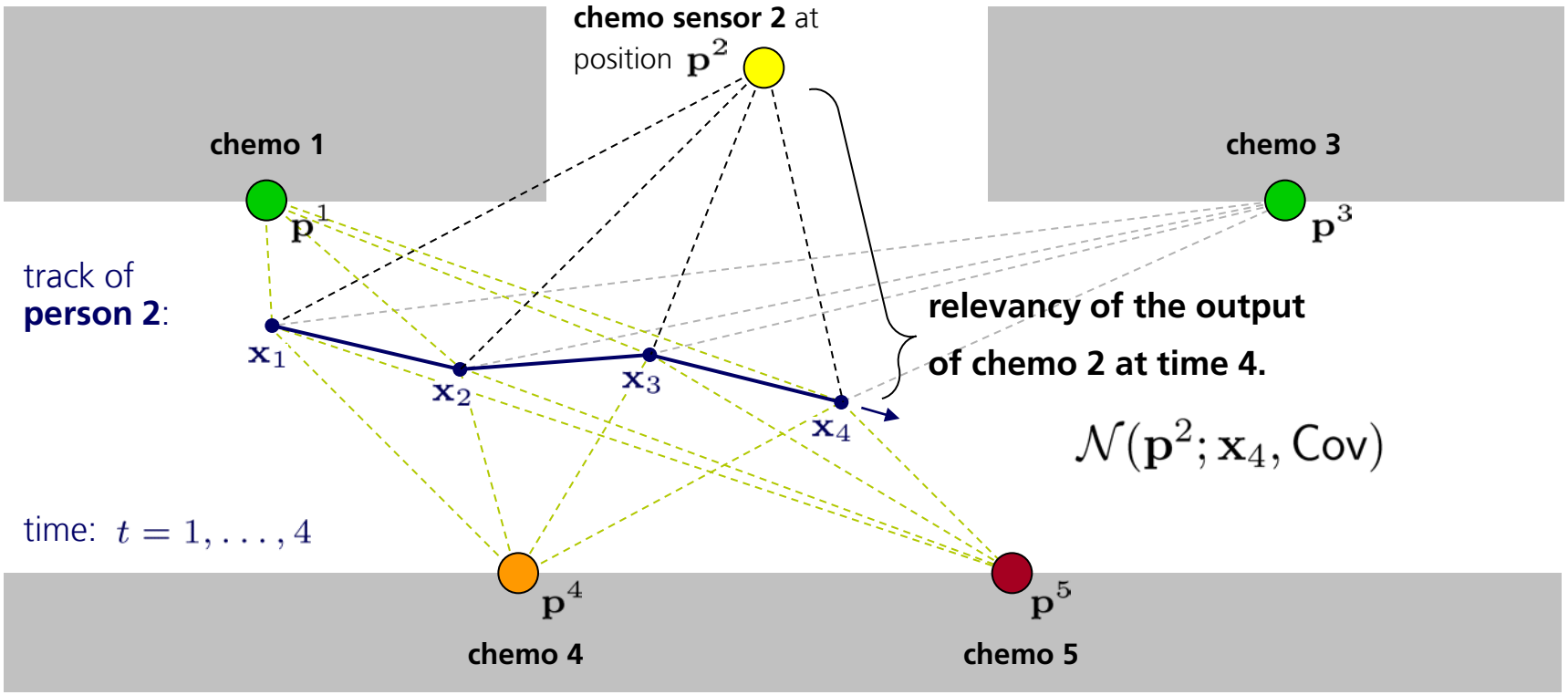
(Streit 1995, Willett et al. 2002/04, Davey, Gray, Luginbuhl ...)

- **Iterative Procedure**
- **Sliding Data Window**
- **Efficient**



Solve the association problem via *Expectation-Maximization*!

Basis: Calculate relevancy of the signatures of each chemo sensor at all instants of time for each individual person.



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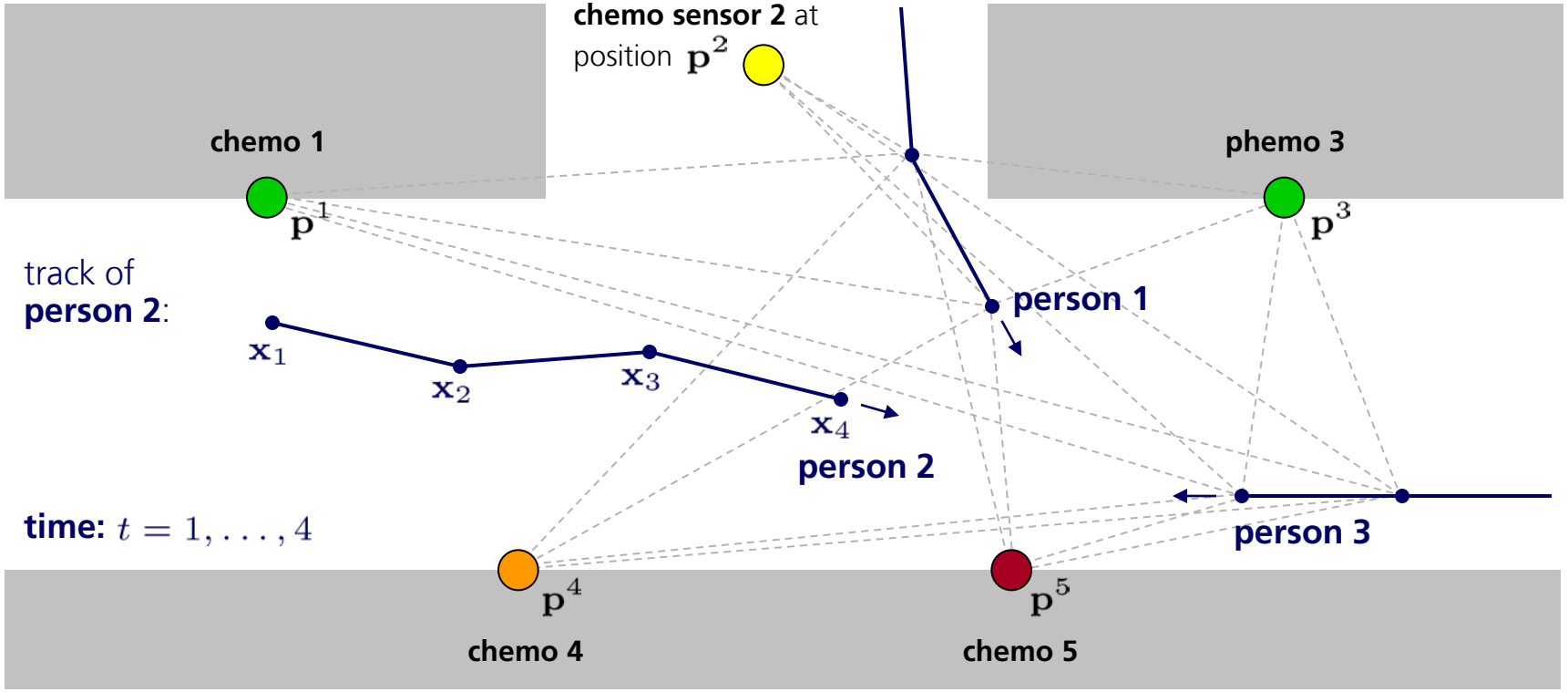
Individual relevancies of the signatures of all chemo sensors at all instants of time for persons 2 and 3 along their tracks:



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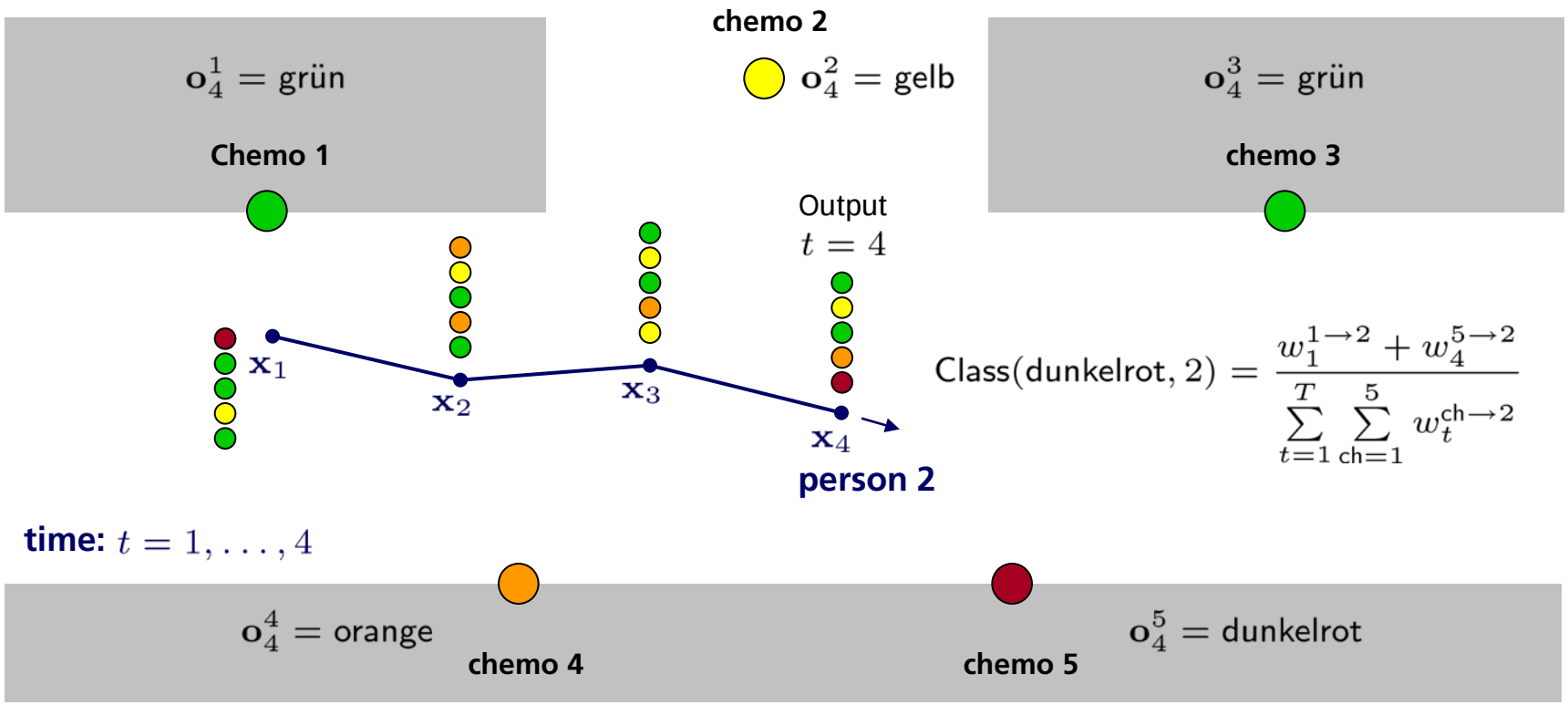
Fusion of position attribut measurements

Iterative calculation of the classification matrix for each person



$$\text{Class}(\text{dunkelrot}, 2) = \frac{w_1^{1\to 2} + w_4^{5\to 2}}{\sum_{t=1}^{T} \sum_{\text{ch}=1}^{5} w_t^{\text{ch}\to 2}}$$

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Fusion: Problems

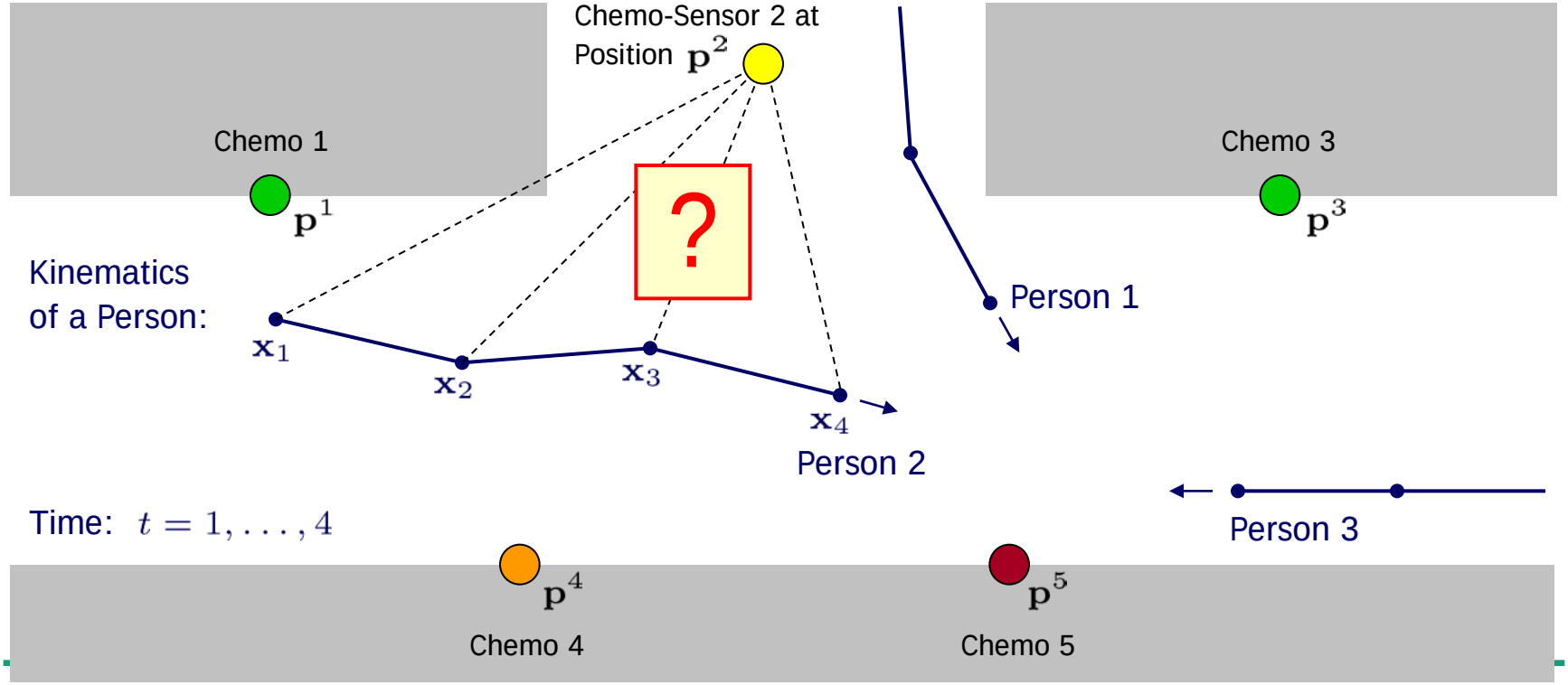
Remark

Assignment Weight Calculation is a difficult task!

Requires Knowledge about the Behavior of Chemo-Sensors

Influences

Not only Distance, but also Velocity, Temperature, **Delay**



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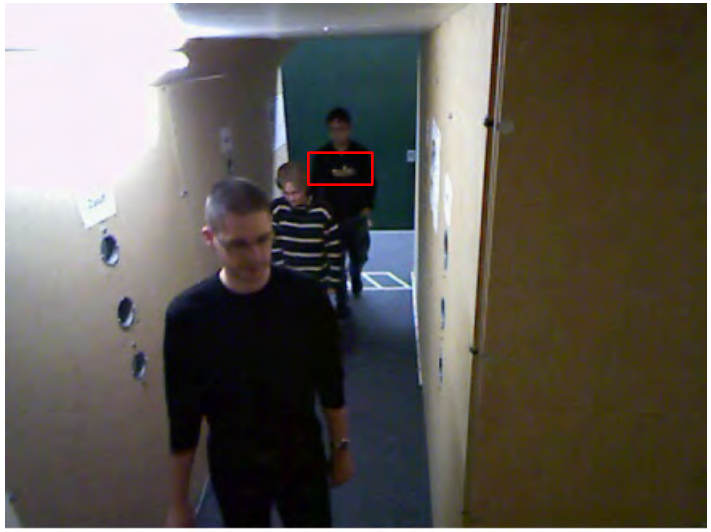
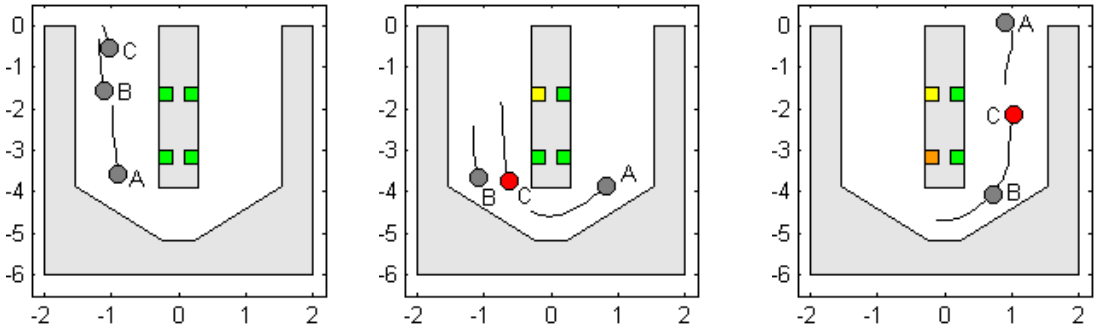
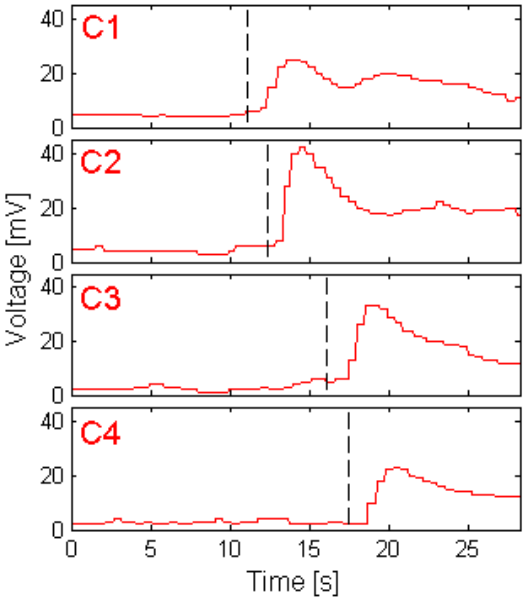
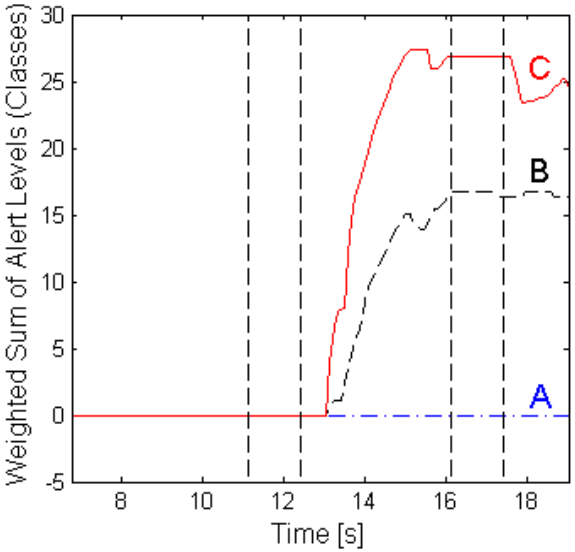
Multiple Sensor Access Control



Source passes coming from behind







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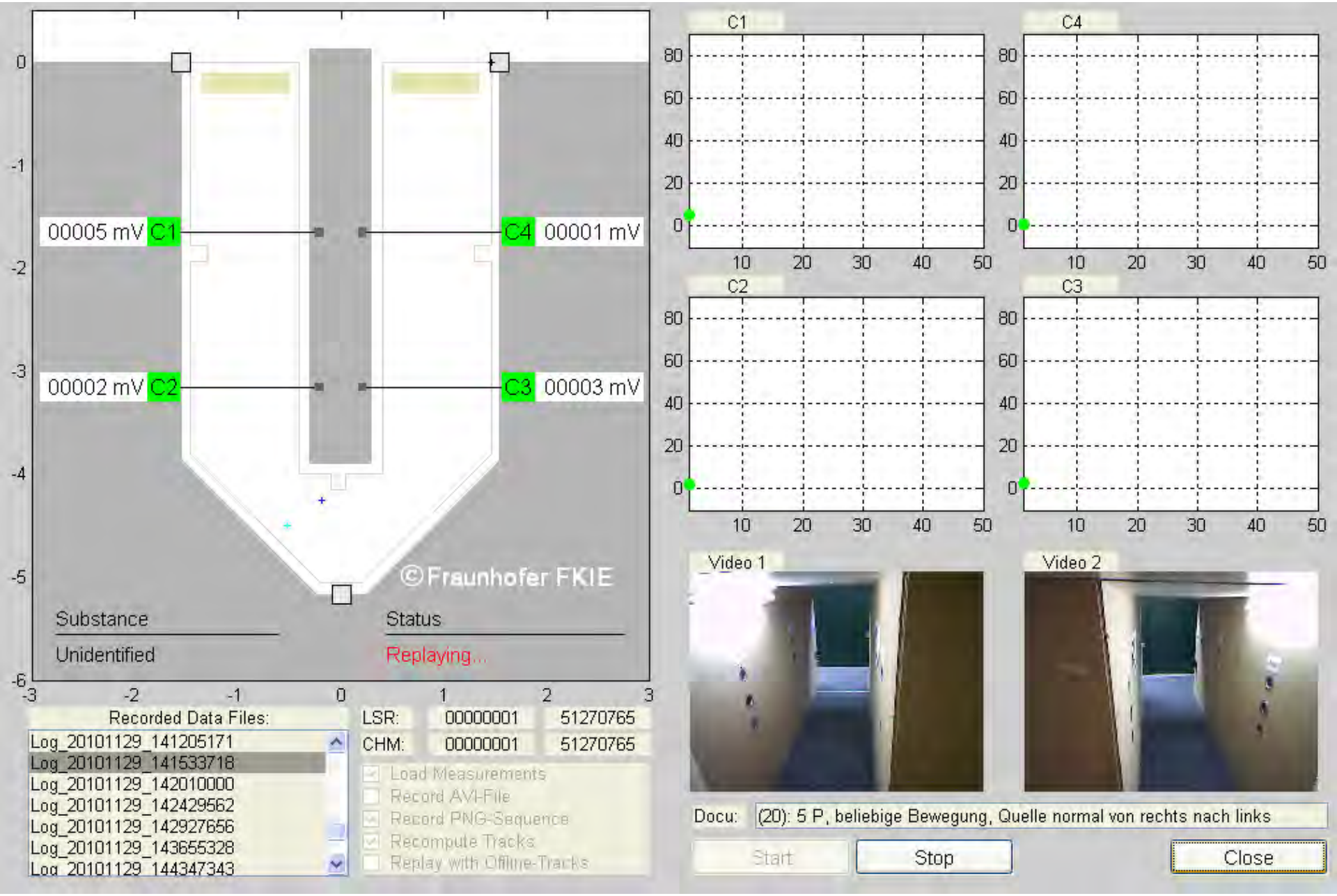

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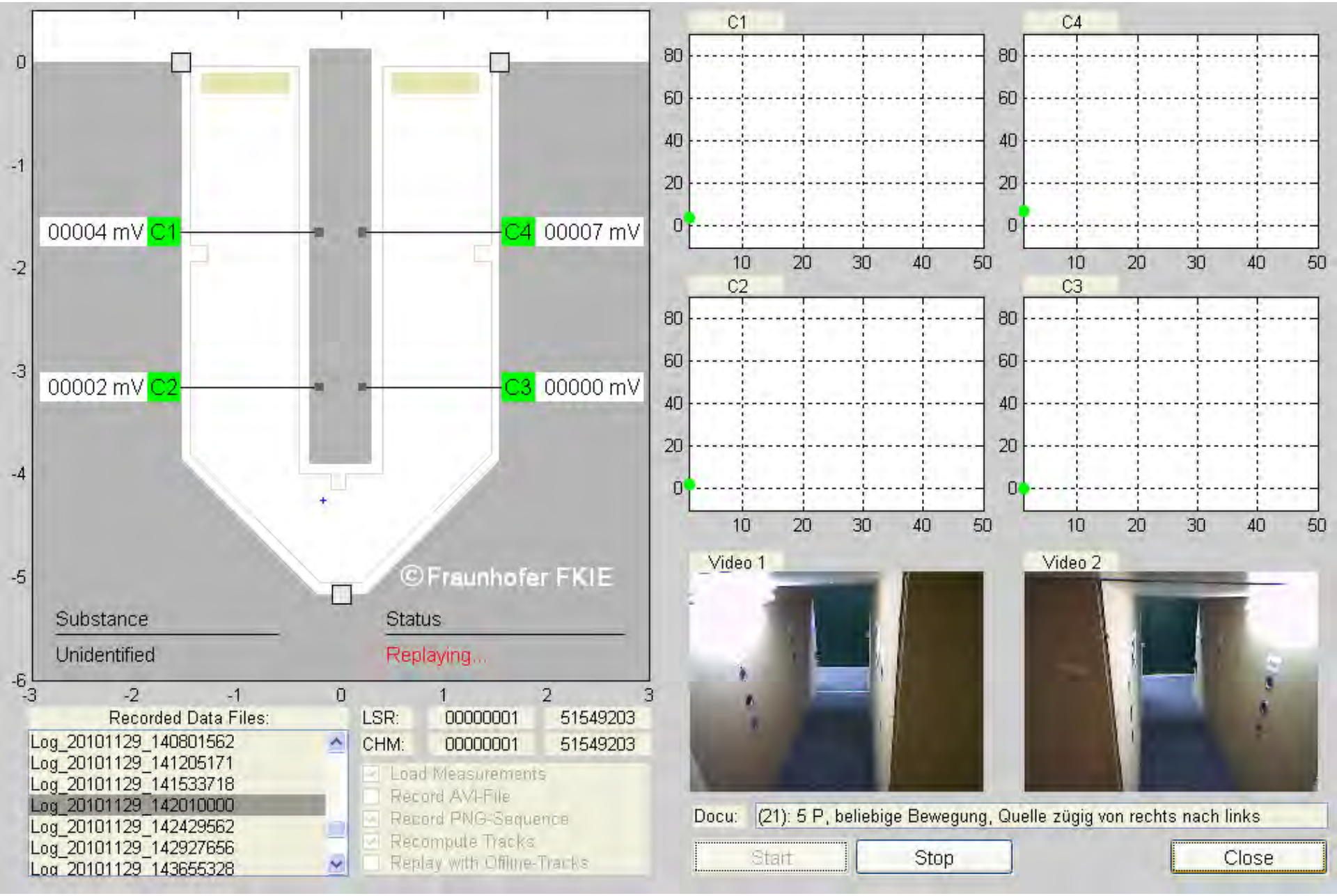

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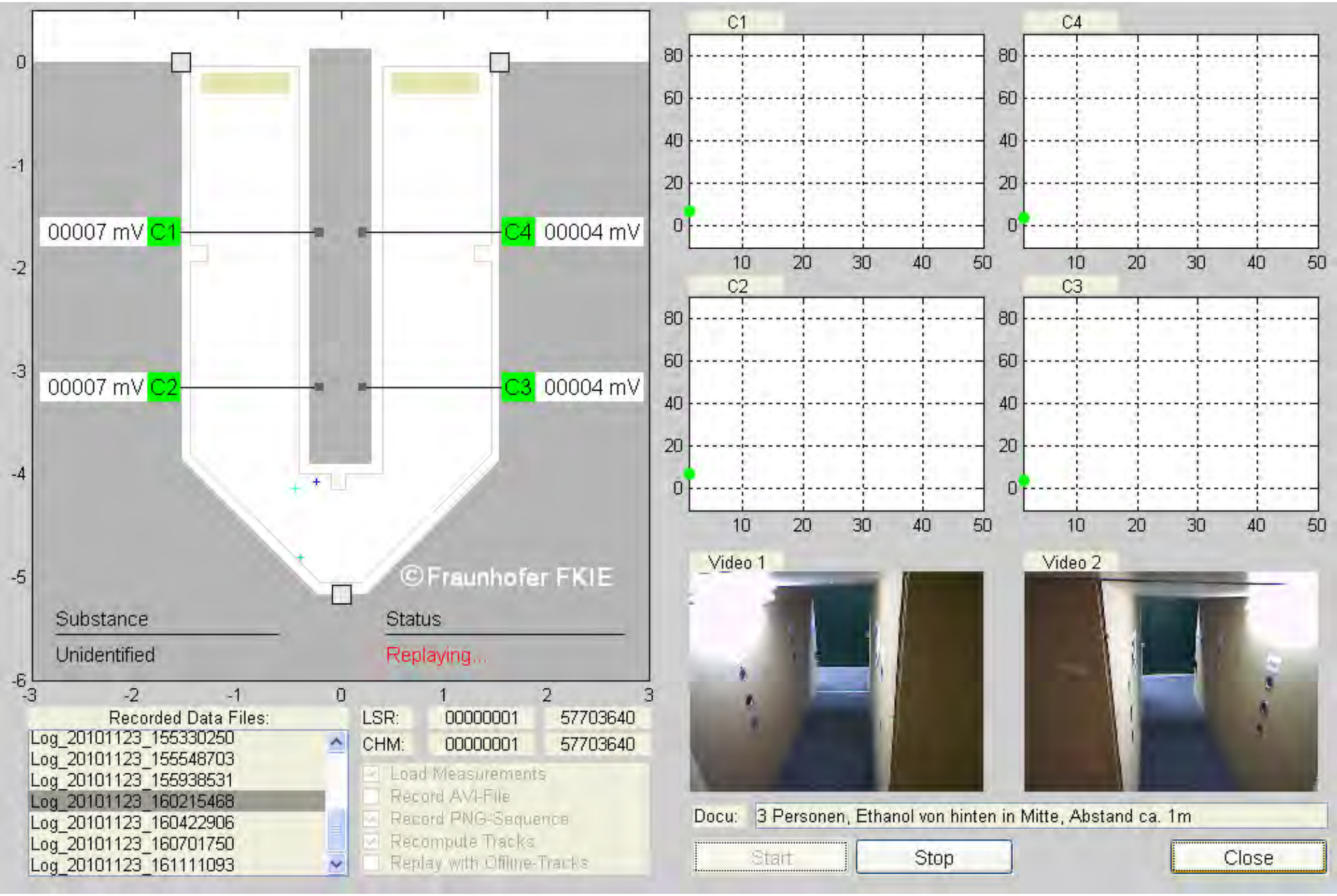

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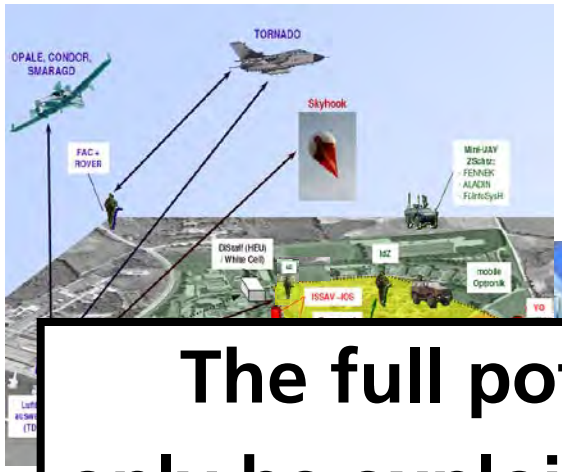
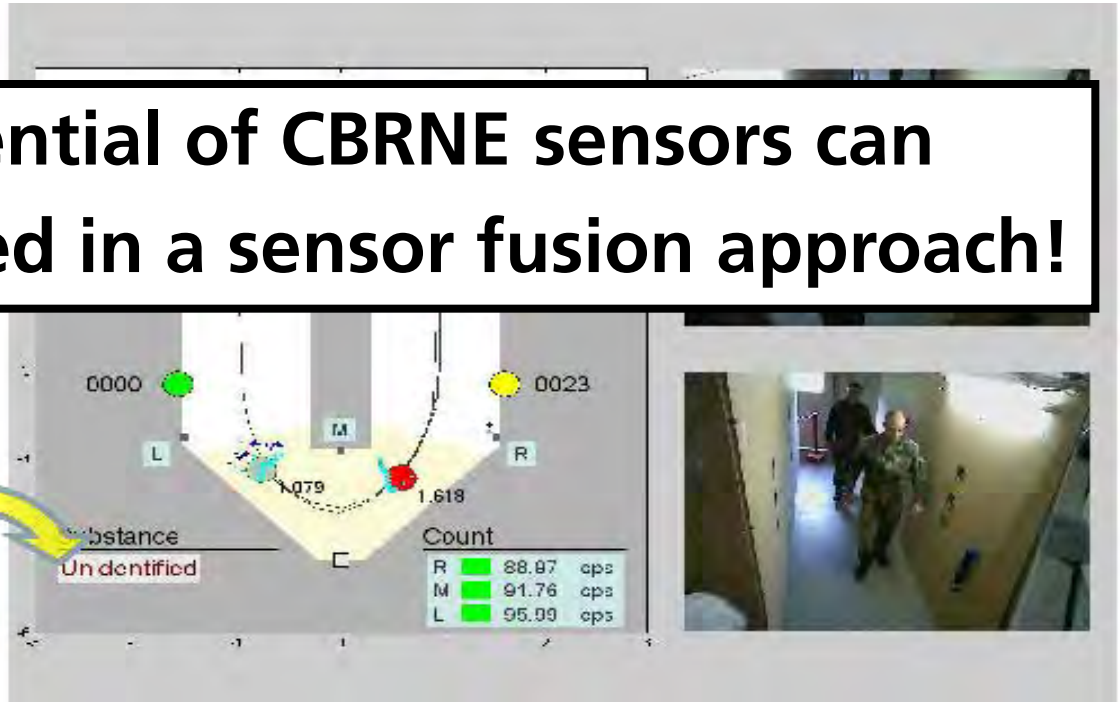
Example: NATO DAT Exercise COMMON SHIELDS



Idea: Use HAMLeT for harbor /camp protection!

5 terrorsists in the scenario, all found no FA

The full potential of CBRNE sensors can only be exploited in a sensor fusion approach!



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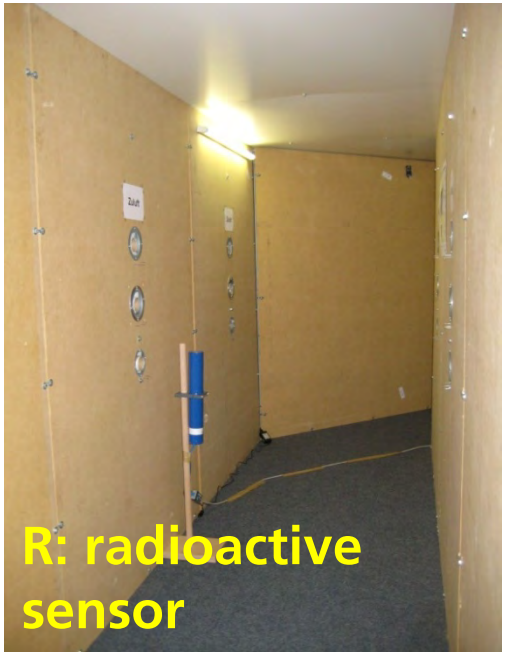
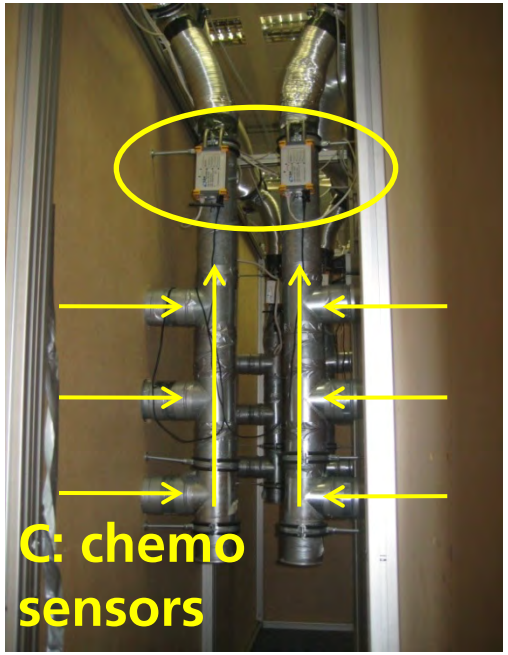
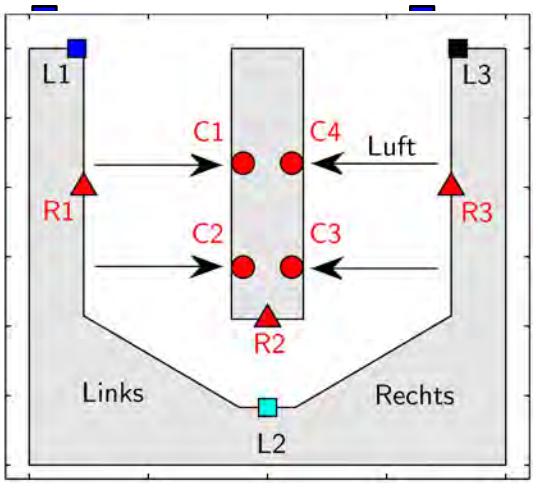
Current Experimental System: HAMLeT Demonstrator







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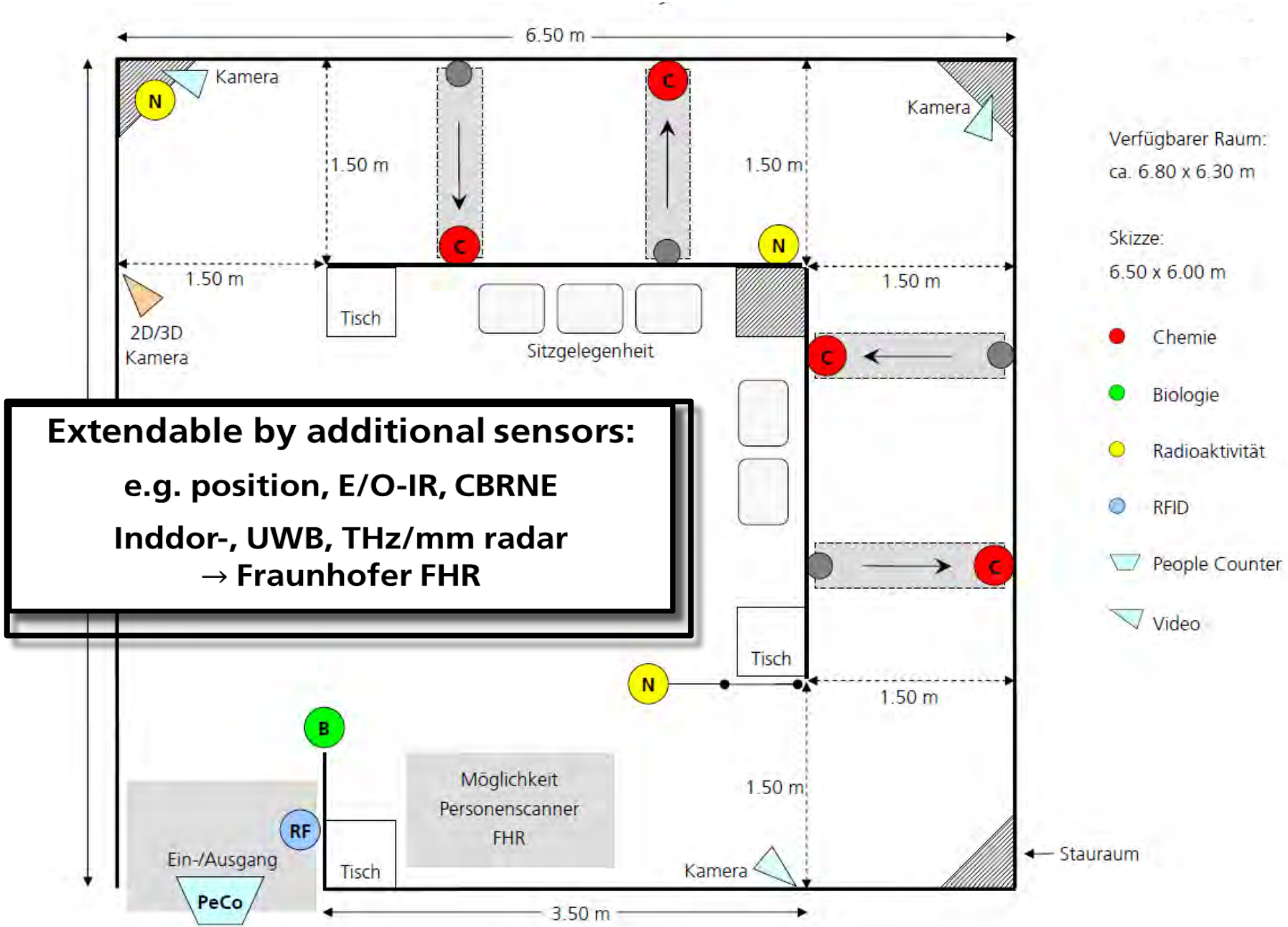
HAMLeT Re-Design: modular, flexible, mobile (under construction)



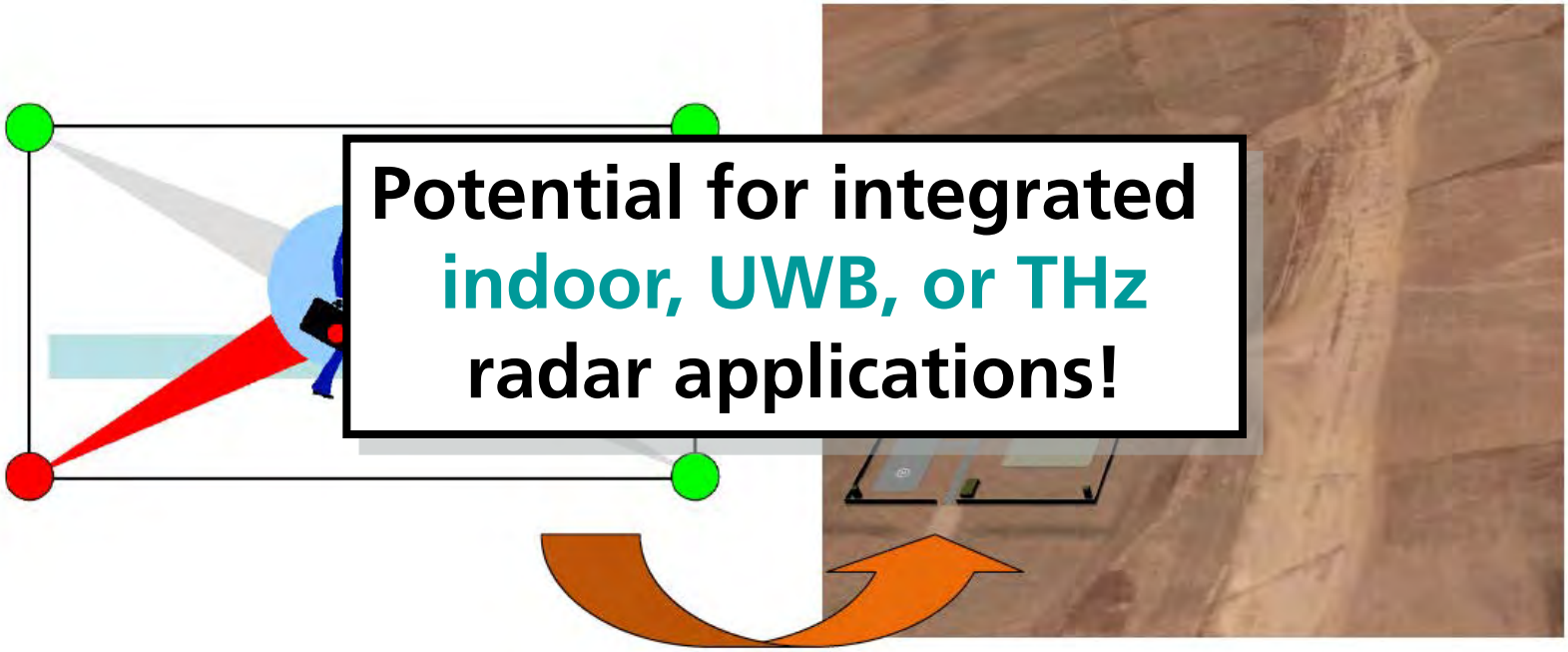
Extendable by additional sensors:

e.g. position, E/O-IR, CBRNE

Inddor-, UWB, THz/mm radar
→ Fraunhofer FHR

„Dual Use“ – Transfer to Defence Applications

Demonstrator for Camp Protection in Meppen



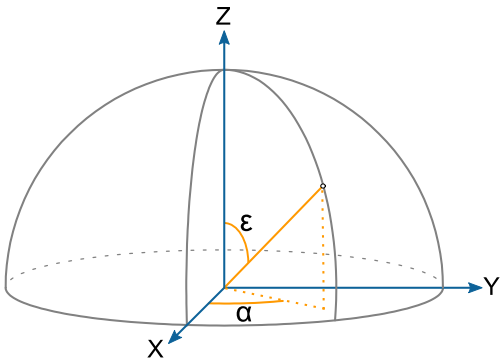
Wieneke, M., Koch, W., Combined Person Tracking and Classification in a Network of Chemical Sensors. *Elsevier International Journal of Critical Infrastructure Protection, vol. 2, nr. 1-2, p. 51-67, May 2009.*

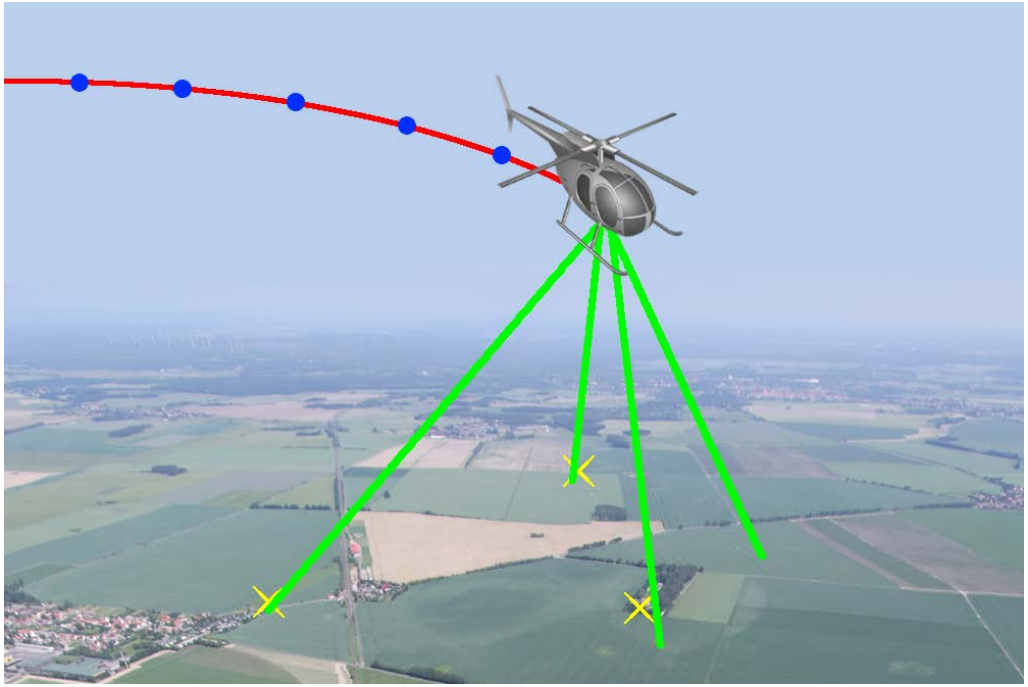
© Fraunhofer FKIE

Multi-object localization and tracking

Input: $Z_k = \{ \mathbf{z}_i \}_{i=1}^{M}, \quad \text{mit} \quad \mathbf{z}_i = (\alpha_i, \varepsilon_i)^T$

Output: $X_k = \{ \mathbf{x}_j \}_{j=1}^{N}, \quad \text{mit} \quad \mathbf{x}_j = (x, y, z, v_x, v_y, v_z)^T$





Sensors:

- EO/IR
- SAR
- Antenna array
- …

Aim:
Localize and track an unknown number of 3D-objects (radio emitters) using 2D-data (bearings).

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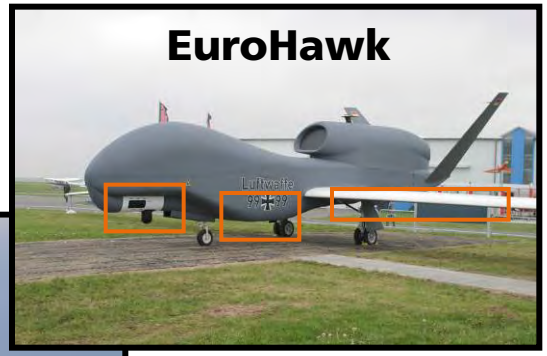
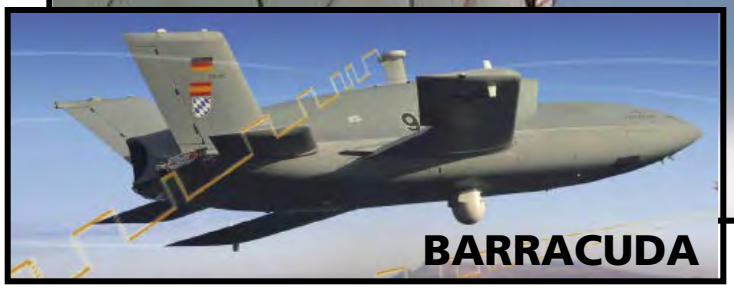
Lokalisierung, Tracking: betrachtete unbemannte Plattformen



manned
UAV demonstrator

(19. August 2010)



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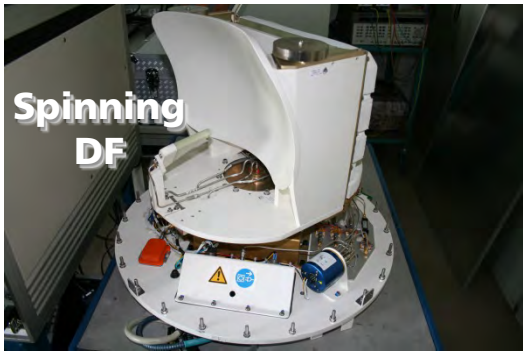
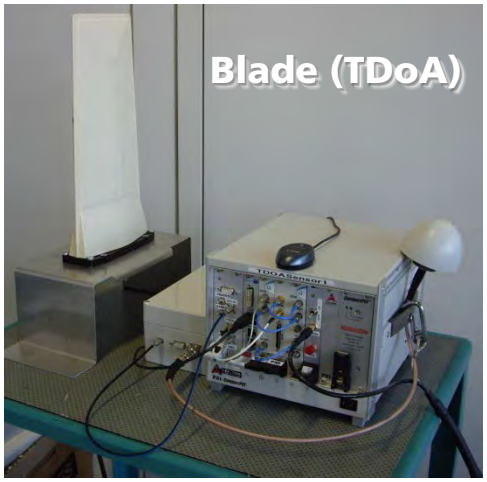
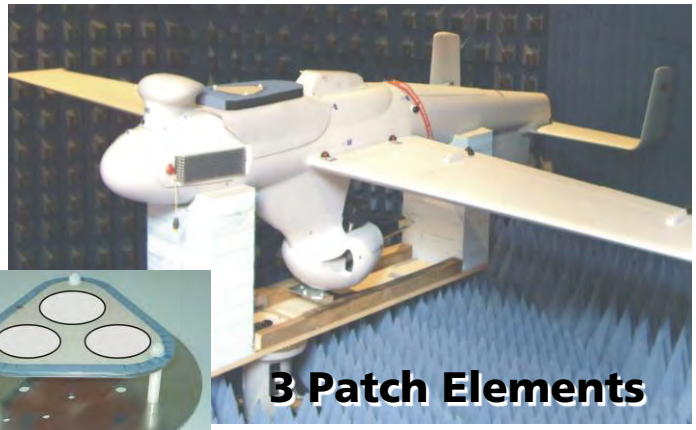
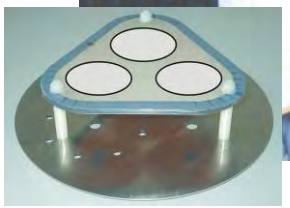
FKIE

RF sensors used in FKIE experiments



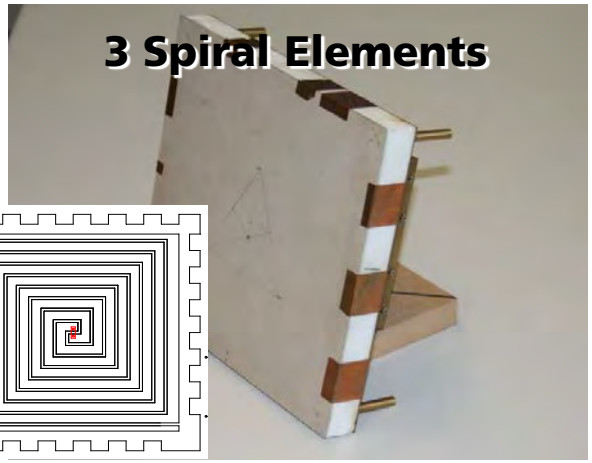




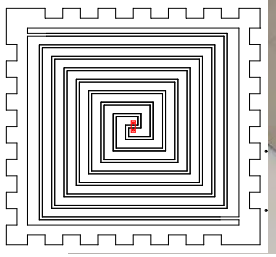


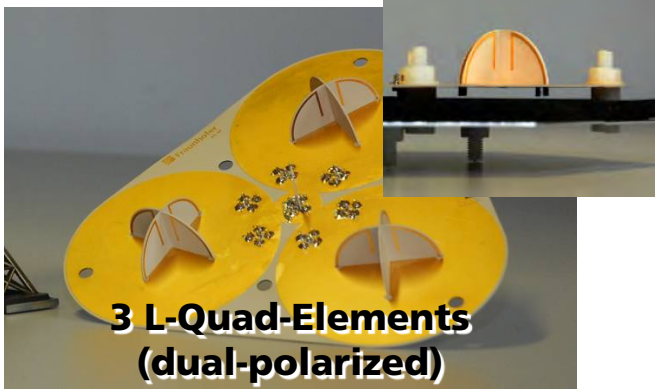
3 Patch Elements

4 L-Quad-Elemente

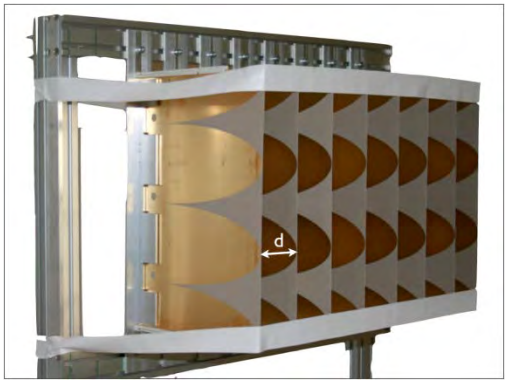


3 Spiral Elements





3 L-Quad-Elements
(dual-polarized)



8 Elements Array

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Field trials for emitter localization with UAS

Spatzenhausen (July 2008)

- Live-demonstration:
- Bearing and localization with UAS **LUNA**

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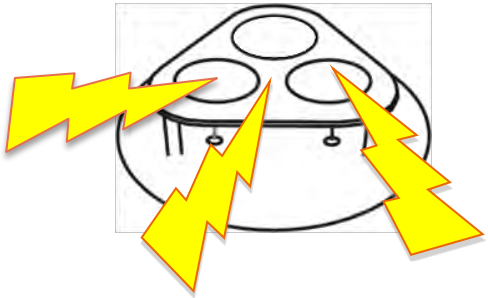
Improvement of localization by sensor data fusion

- **Aim:**
  - Localize an unknown number of emitters with bearing measurements
  - Improvement of the results by fusing data of heterogeneous sensors
- **Used sensors:**



Antenna array:

- Measures radio signals
- Unique
- Inaccurate

Camera:

- Not measuring radio signals
- Ambiguous
- Accurate

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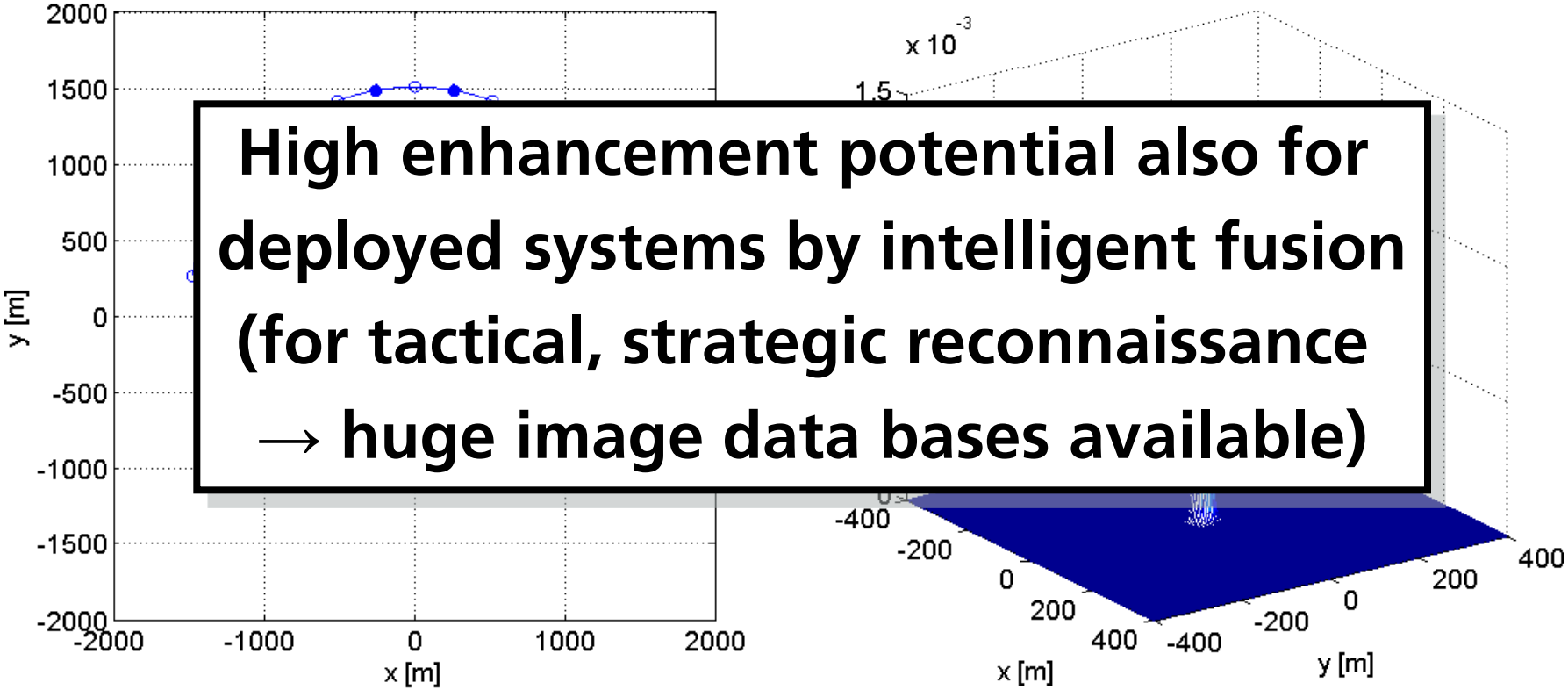
Simulation: Fusion SIGINT+IMINT (→ MiSAR)

DOA sensor
- observation point

Image sensor
- ○ observation point

field of view

localization



High enhancement potential also for deployed systems by intelligent fusion (for tactical, strategic reconnaissance → huge image data bases available)

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Object detection with a learning algorithm

Positive test images (#185)

Negative test images (#600)

Input image

Extract feature vectors

Extract feature vectors

Slide a window over the image

Build an SVM model

Compute feature vector for window

Classify each window

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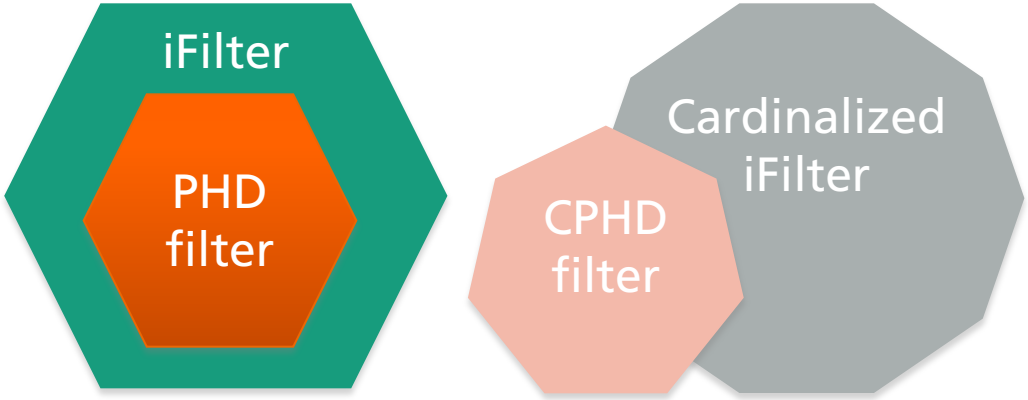
Multi-object localization and tracking

Input: $Z_k = \{ \mathbf{z}_i \}_{i=1}^{M}, \quad \text{with} \quad \mathbf{z}_i = (\alpha_i, \varepsilon_i)^T$

Output: $X_k = \{ \mathbf{x}_j \}_{j=1}^{N}, \quad \text{with} \quad \mathbf{x}_j = (x, y, z, v_x, v_y, v_z)^T$

Method: Approximation of the multi-object multi-sensor Bayes filter

Poisson Point Process (PPP) particle filter



first order appr. higher order appr.

Properties

- ✓ no linearization errors
- ✓ no data association
- ✓ asymptotic efficient
- ✓ fast (parallelizable)
- ✓ simple initialization

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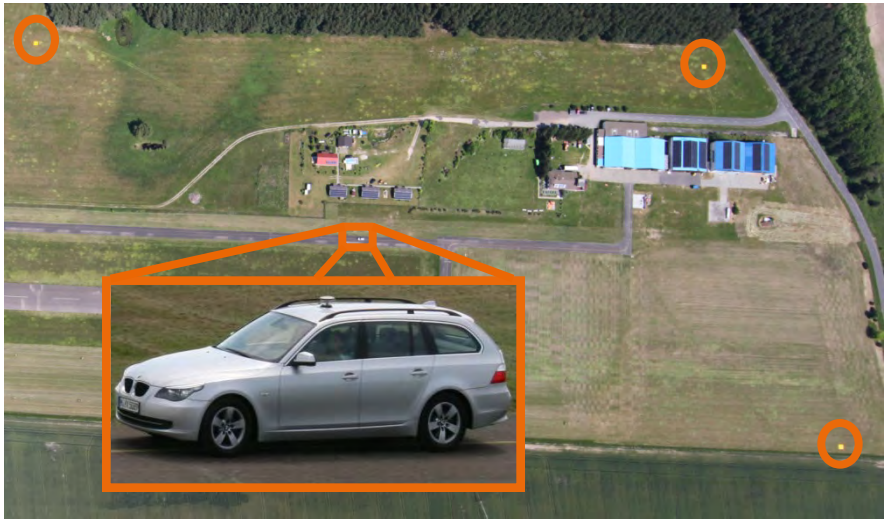
Field trials for emitter localization with PPP's

Zellendorf (July 2010)

- Localization with UAS demonstrator **Smaragd**
- Three stationary and one moving emitter
- Bearing measurements from 4-element antenna array and camera system



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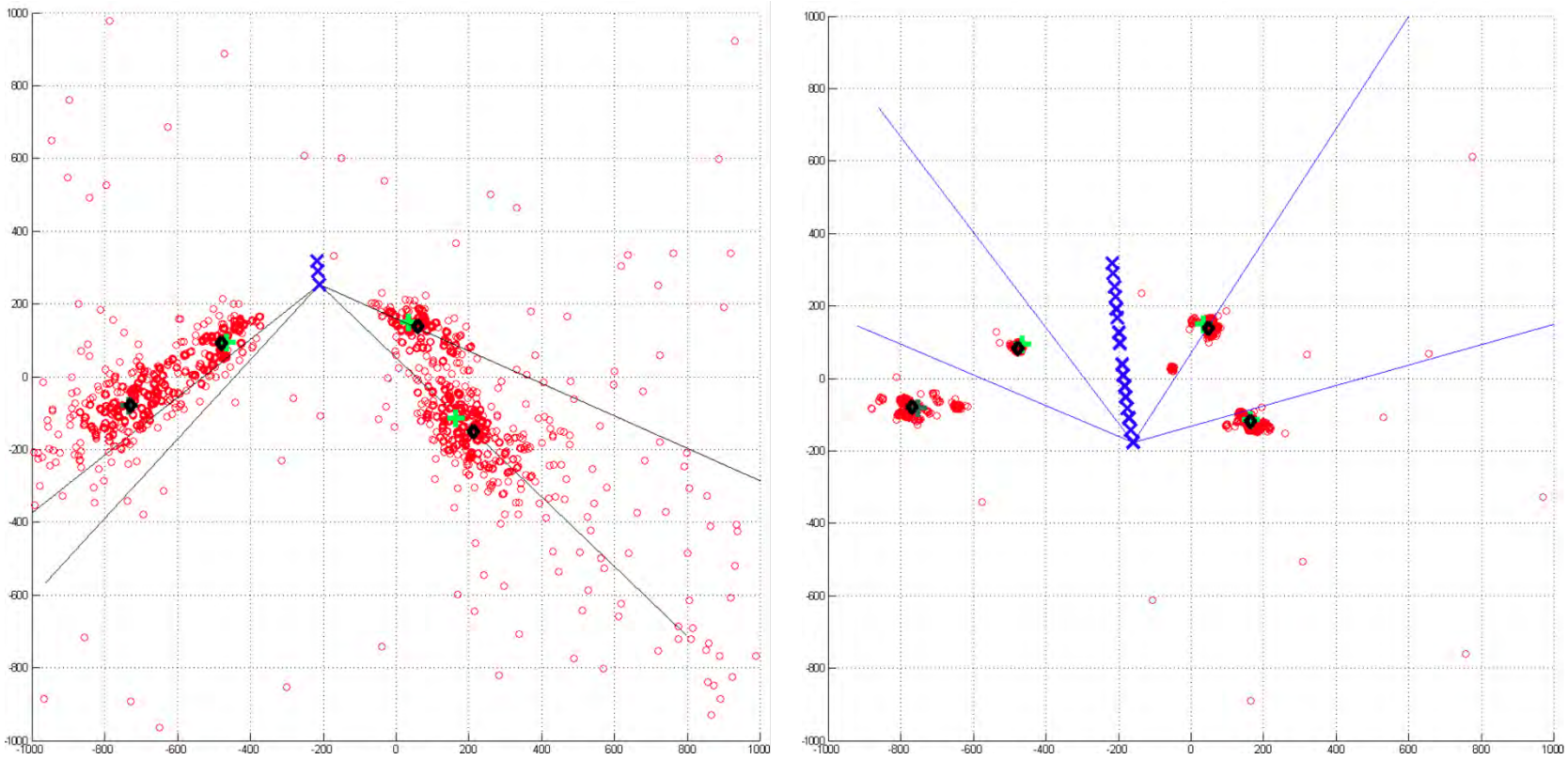
Results multi-target object localization



Particle cloud evolution for different time steps (visualization of xy-plane)

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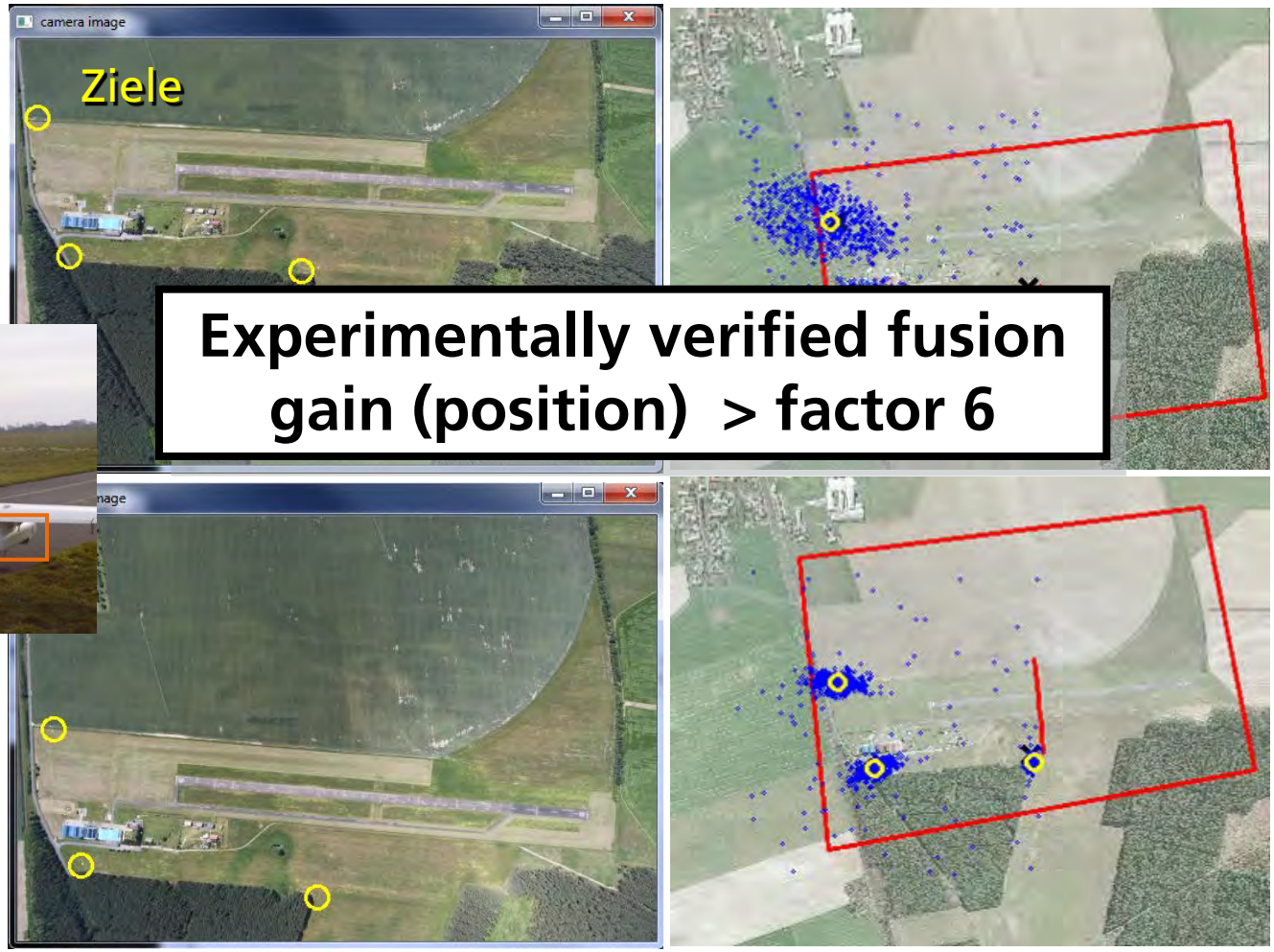
Fusion experiment: November 2010

manned UAV demonstrator

- **Image sensor**
- **Array sensor**



Experimentally verified fusion gain (position) > factor 6

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Localization and tracking
From the PHD to the iFilter

Only heuristics available

- What is the clutter model in images?
- How to model target birth in arbitrary scenarios?

Estimate parameters of both models

„The PHD-filter is a special case of the intensity filter (iFilter), if derived through Poisson point processes.“

R. Streit, Fusion 2008

Properties of the iFilter:
- same as PHD, but
- estimates clutter model
- estimates birth model
- appears to be more stable

See Marek Schikora's Paper at Fusion 2011!

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Performance enhancement by Multi-UAS

Cooperation of platforms with homogeneous payloads

- DOA measurements
- TDOA measurements
- Combination of both

Cooperation of platforms with heterogeneous payloads

- Direction finding and image sensors
  - Adjustment of image sensor by direction finding sensor
  - Fusion SIGINIT / IMINT

Combination of fixed-wing aircraft and/or copter

Consideration of maneuvering targets

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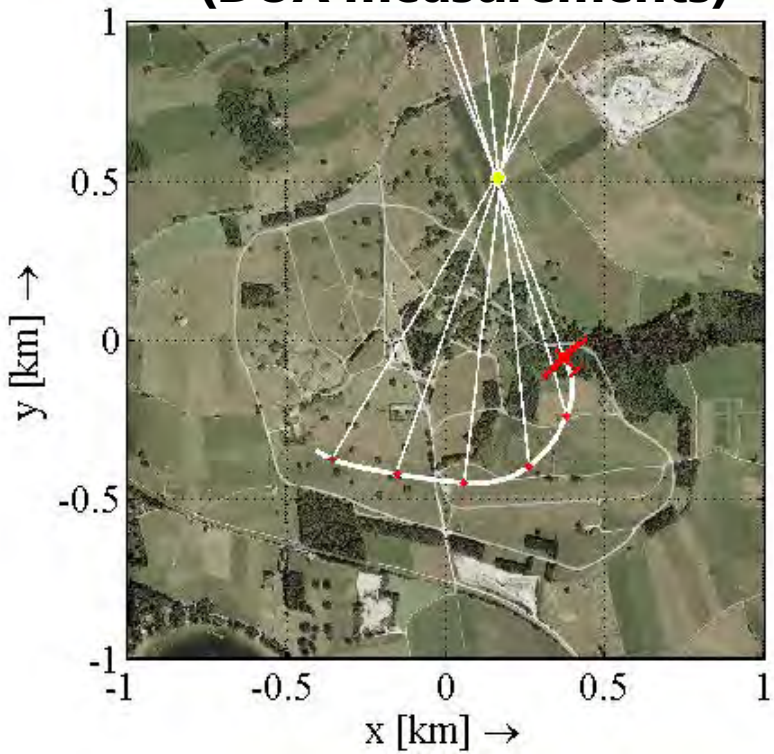
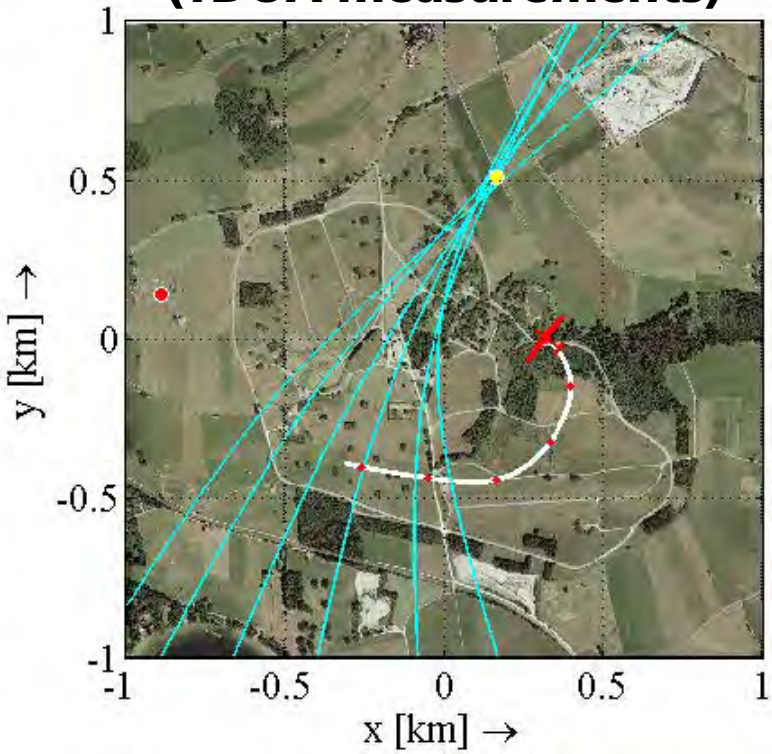
Cooperation of platforms with homogeneous payloads

DOA and TDOA measurements

Triangulation (DOA measurements)



Trilateration (TDOA measurements)



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Cooperation of platforms with homogeneous payloads
Combination of DOA and TDOA measurements

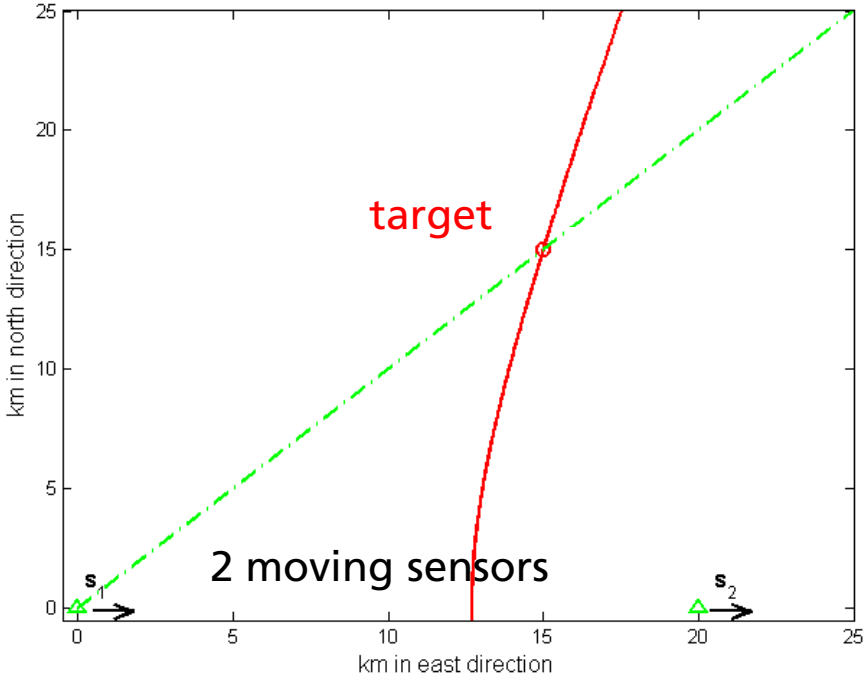
Example:

Two moving sensors

- both measure TDOA
- one measures DOA

Significant gain in accuracy

TDOA & **DOA** measurement



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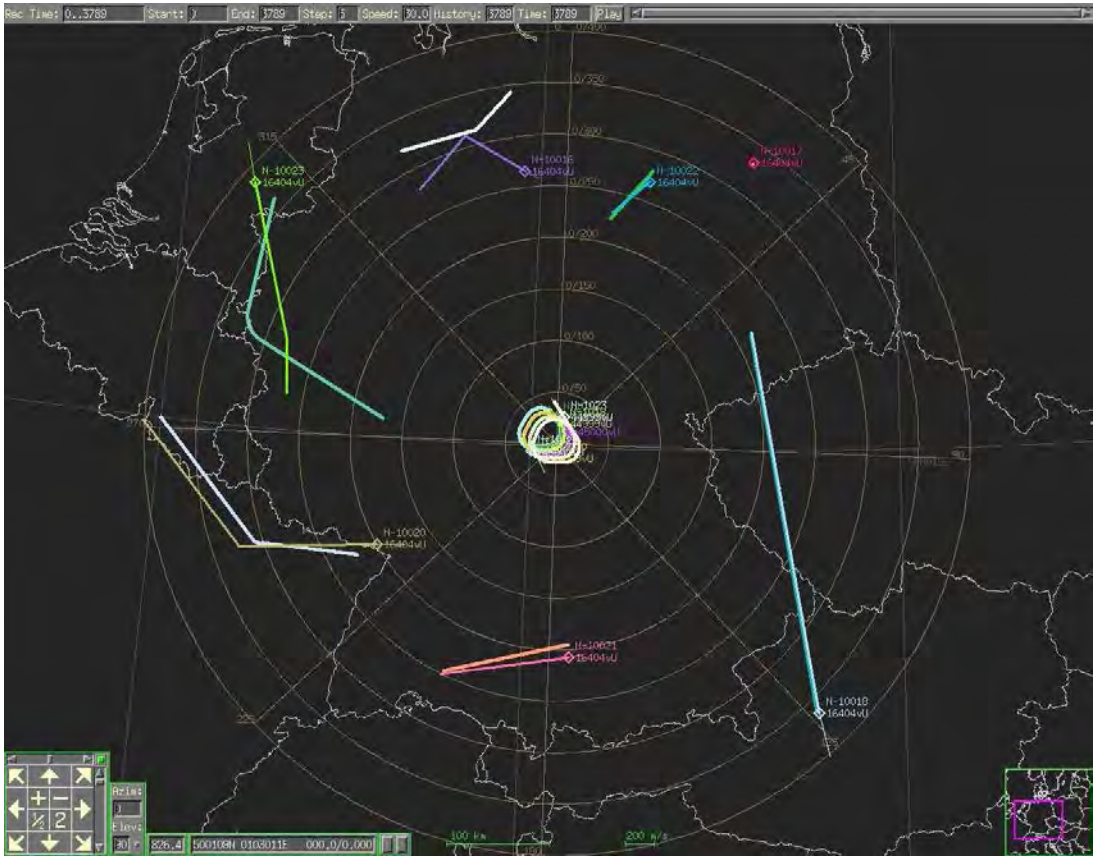
Kontext GIADS: Emitter-Lokalisierung/Tracking - Fusion of AoA, TDoA



Azimut-only Messungen
Trajektorien des Sensors (Bildmitte) und der Emitter (mit Symbol am Ende der Spur) im Vergleich mit den errechneten Zieltrajektorien.

Kooperation

CASSIDIAN CY

Problem

Azimut-only Messungen:
- **Problemen bei Manövern**
- **Geometrieabhängigkeit**

Lösungsansatz

Fusion von AoA- und TDOA-Messungen

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CASSIDIAN AN EADS COMPANY

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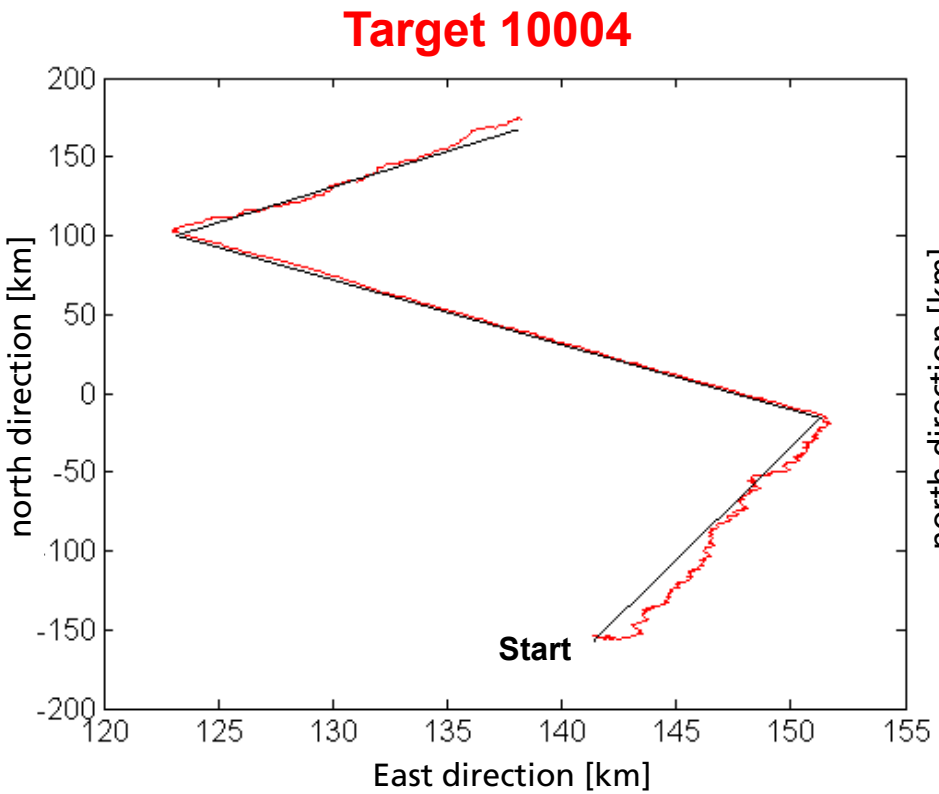
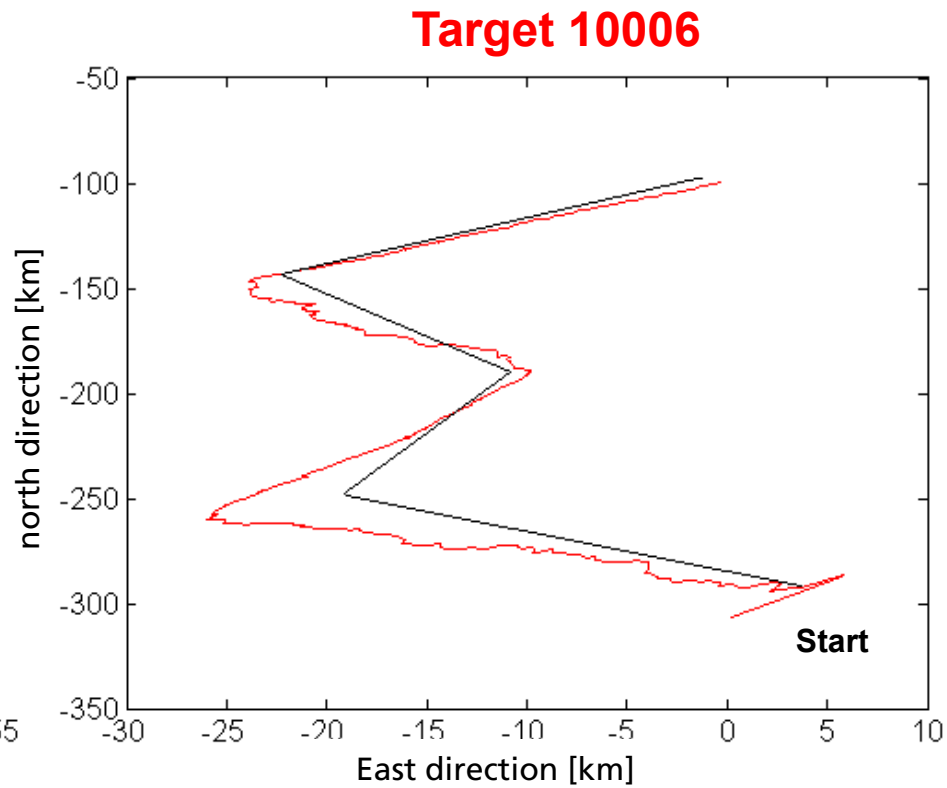
Examples for selected targets





— True trajectorie

— Localization based on bearings and TDOA

Localization accuracy of about 2-8 km

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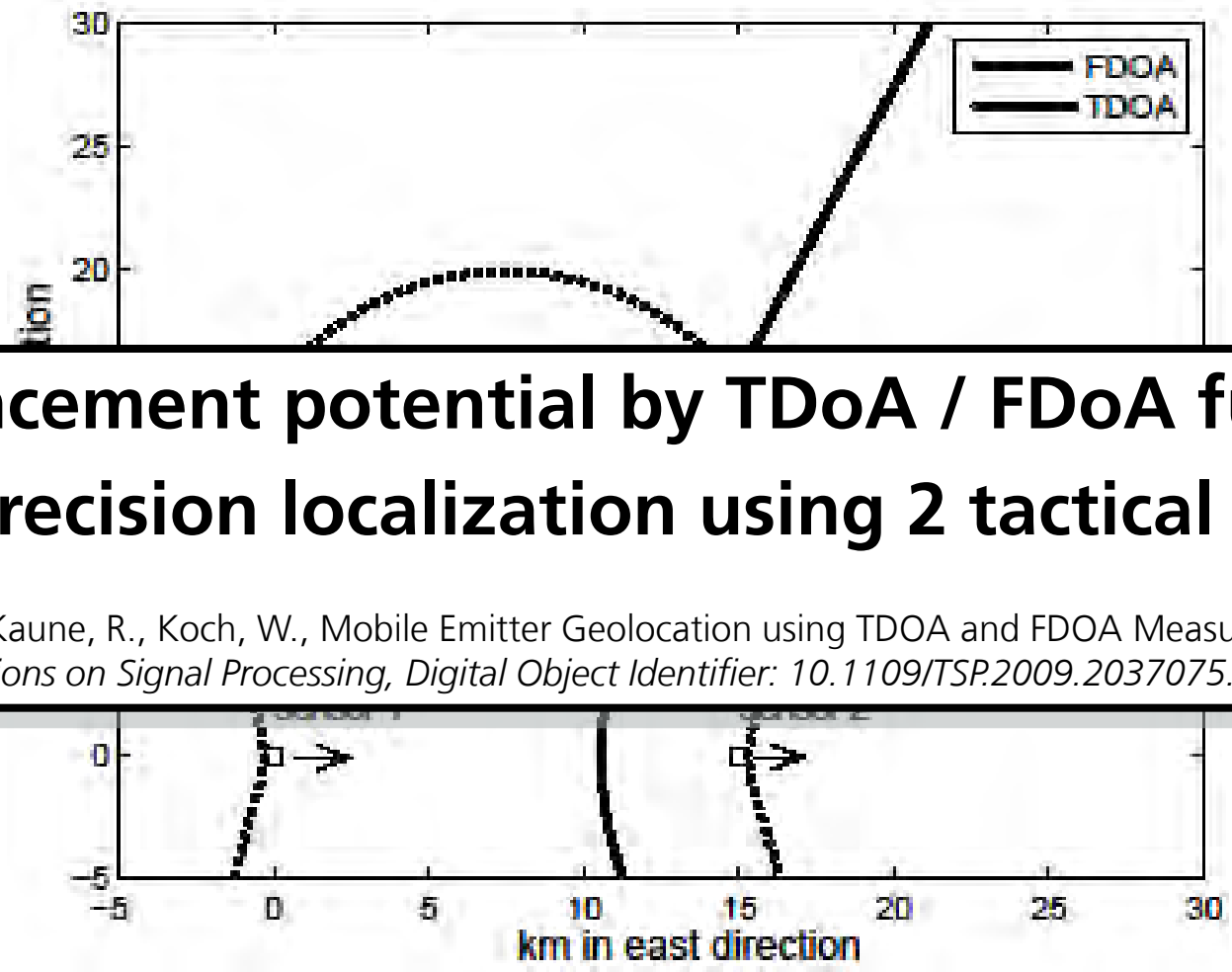
Emitter Localization: Fusion of AoA, TDoA, FDoA



Enhancement potential by TDoA / FDoA fusion:
Fast precision localization using 2 tactical UAVs

Musicki, D., Kaune, R., Koch, W., Mobile Emitter Geolocation using TDOA and FDOA Measurements. *IEEE Transactions on Signal Processing, Digital Object Identifier: 10.1109/TSP.2009.2037075.*

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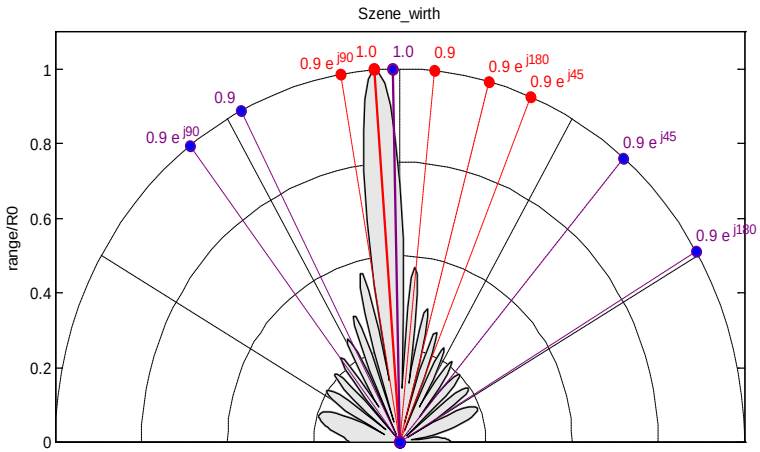
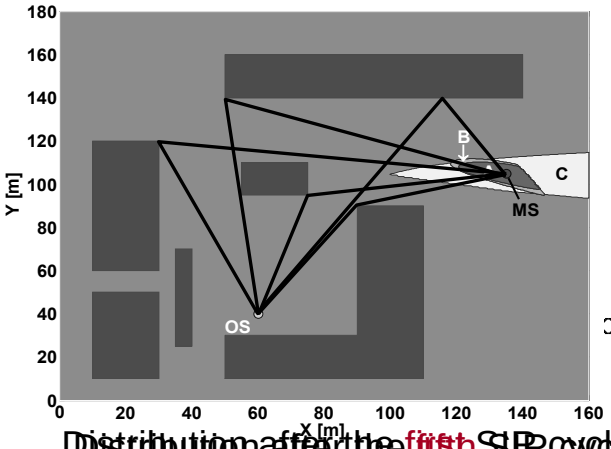
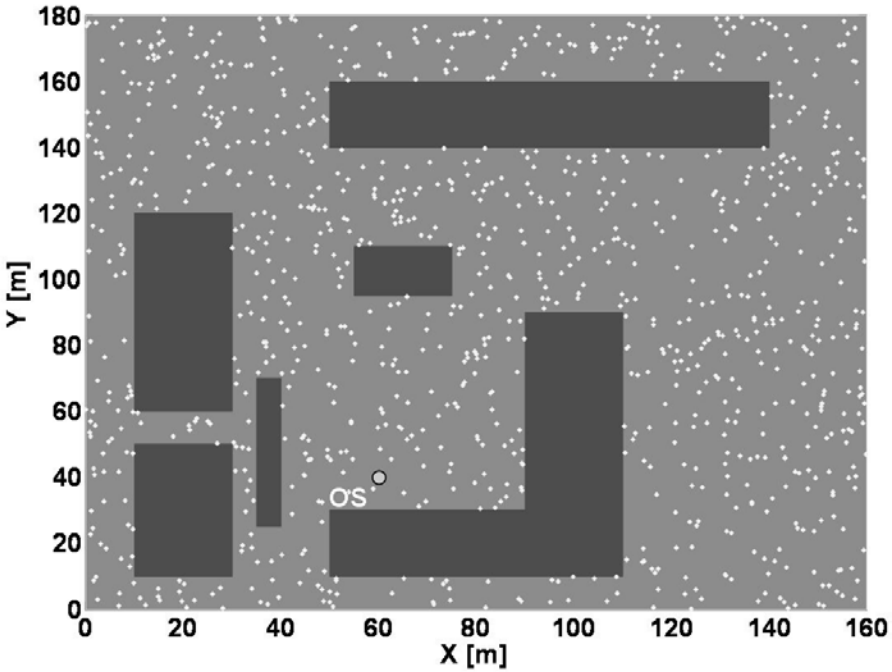
GAMMA: Urban Emitter Localization

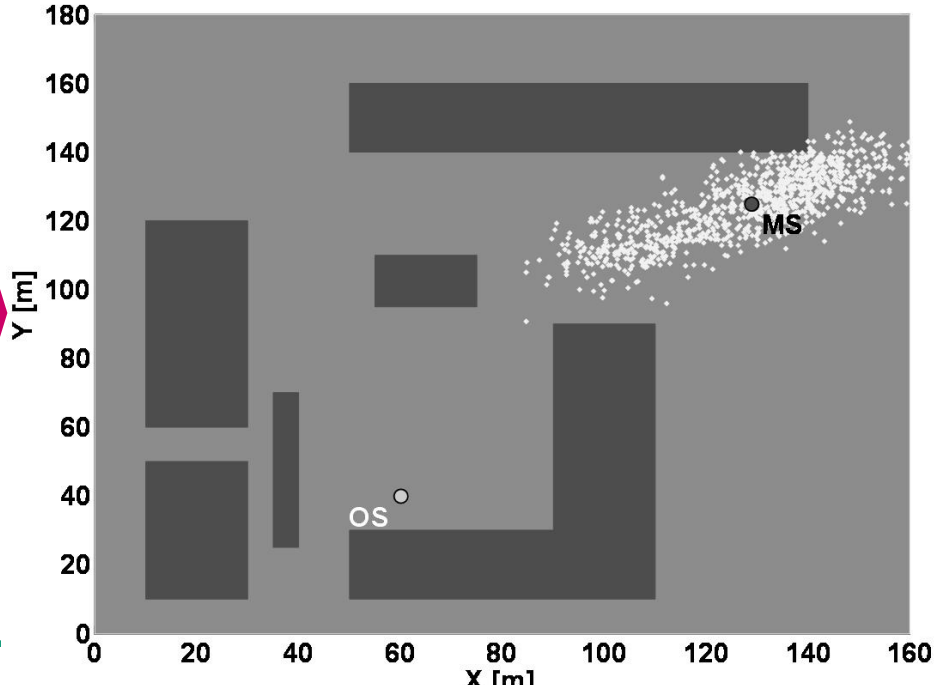




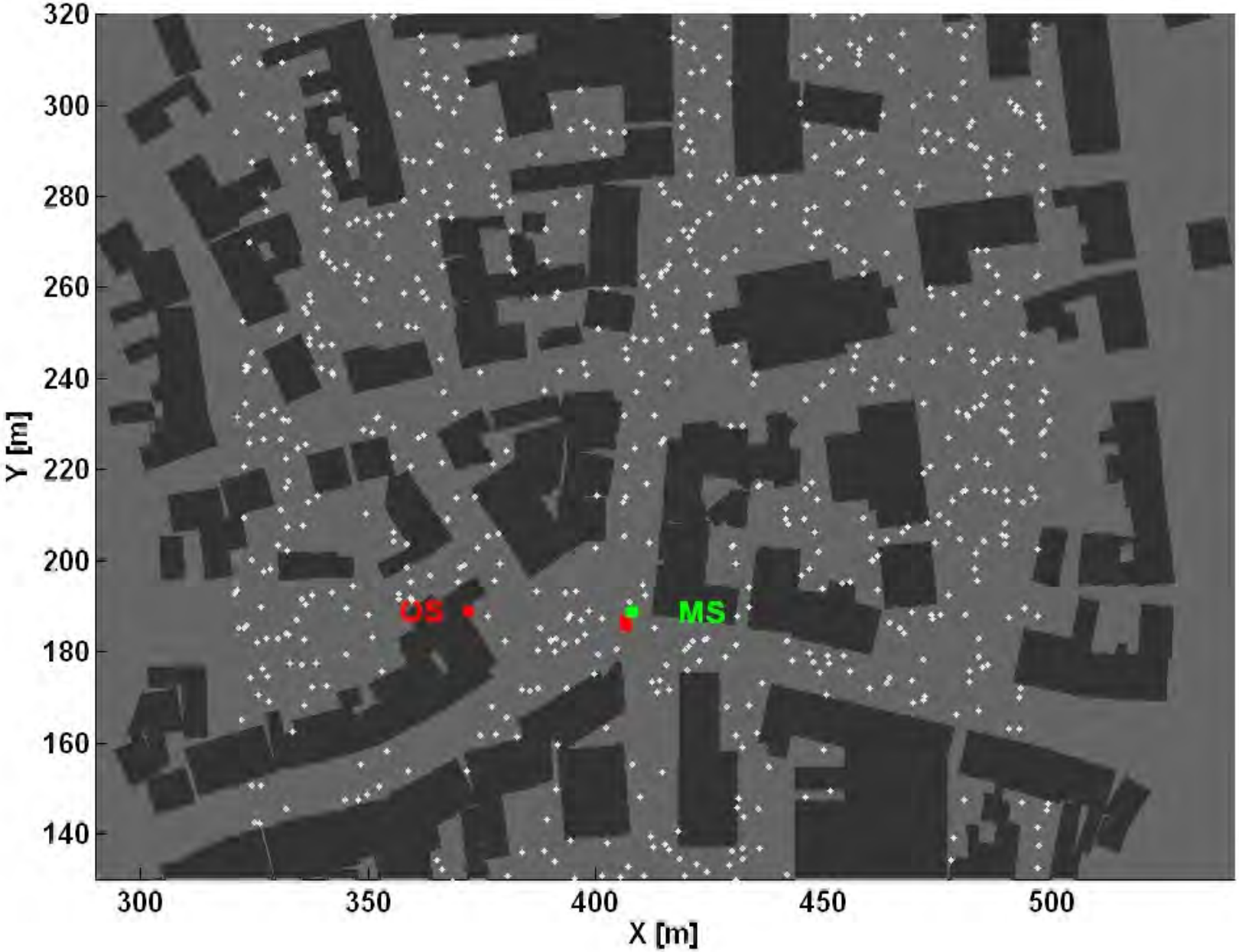
C:\Kopernikus\Film Multipath.avi

Distribution after the fifth SIR cycle





Algeier, V., Demissie, B., Koch, W., Thomä, R., State Space Initiation for Blind Mobile Terminal Position Tracking. *EURASIP Journal on Advances in Signal Processing, Special Issue on Track-before-Detect Algorithms, Volume 2008 (2008),ID 394219.*


320
300
280
260
240
220
200
180
160
140
Y [m]
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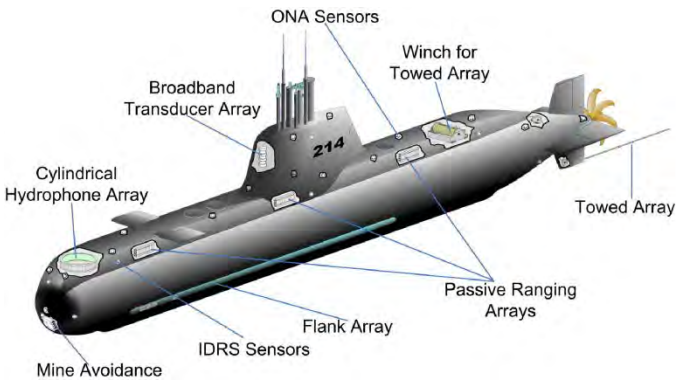
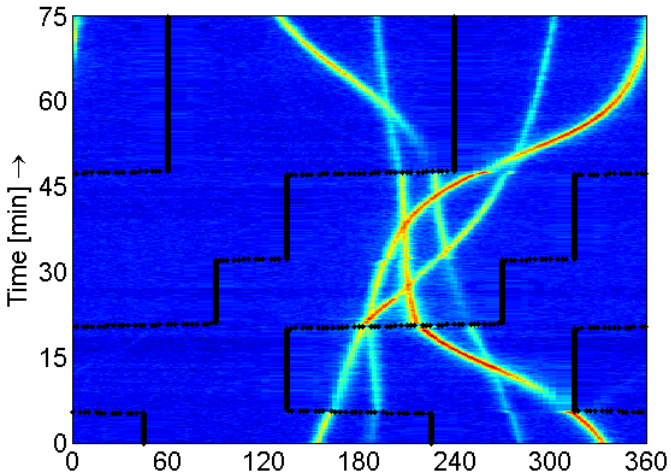
350
400
450
500
X [m]
OS
MS

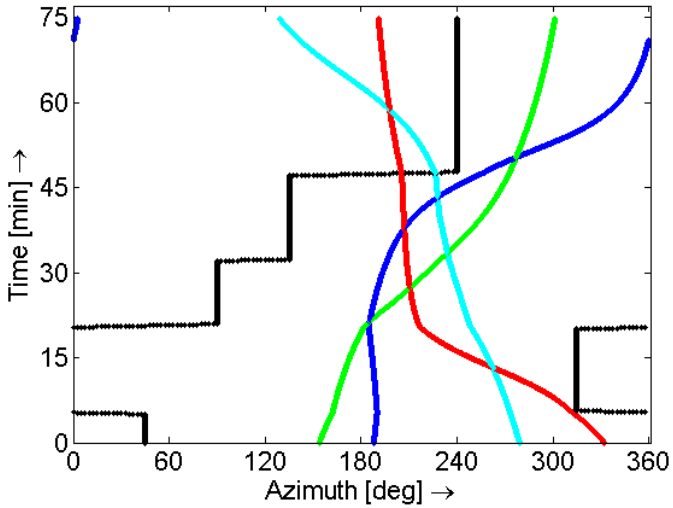
Industry Study, ATLAS

Bearings, Association, Localization

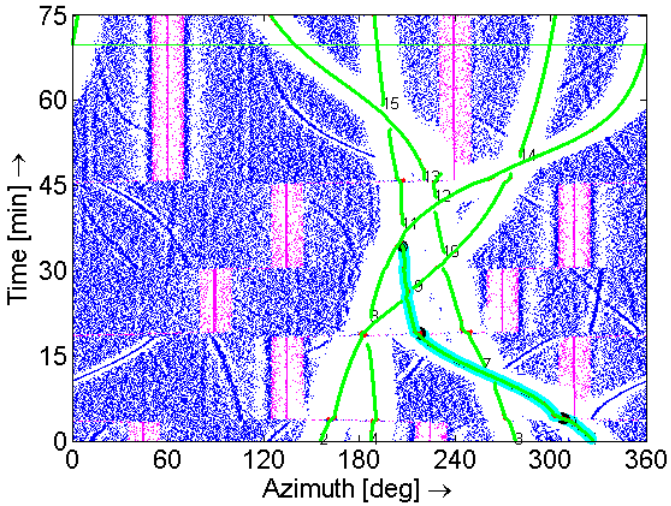


Breitbandpeilung für beide Flankarrays





Peildatenassoziierung mittels MHT



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A joint company of ThyssenKrupp and EADS

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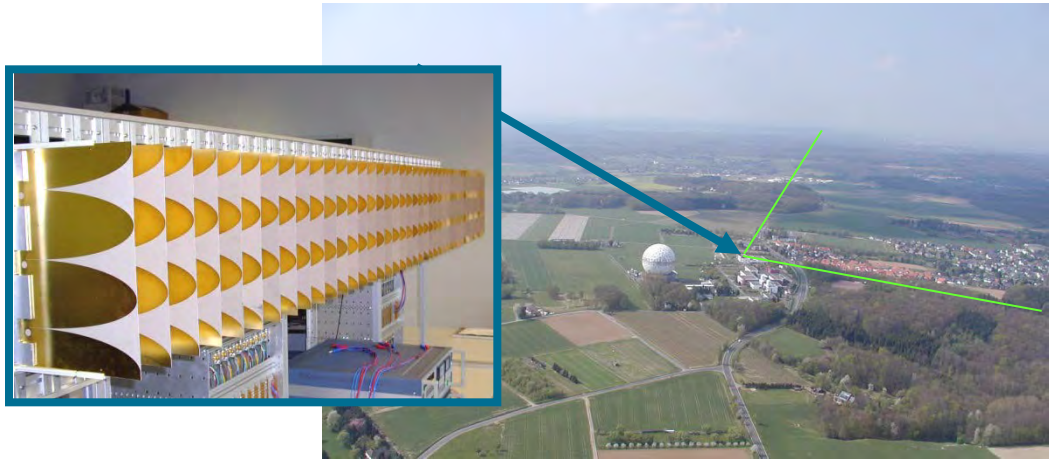
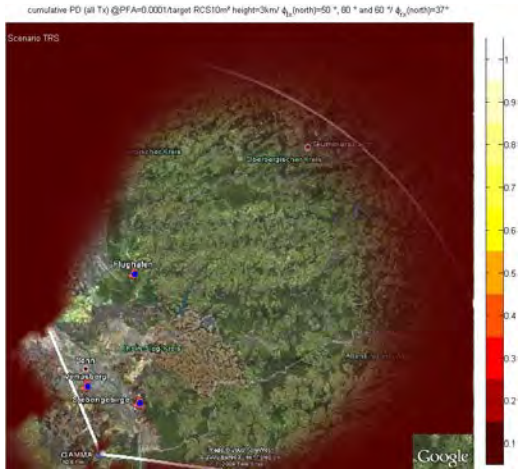
A Look at GSM Illuminators for Cover Observation

- **Development of a demonstrator for GSM passive radar**
- **Tracking / De-ghosting** **(also for FHR: DAB / DVB frontend)**

GSM Mobile Phone Base Stations

- ✓ **Illuminators even in remote areas: OOA, littoral regions**
- ✓ **Frequency diversity of illuminators: less ghosts**
- ✓ **"Radar"-frequency 1.8 GHz → good angular resolution**





(**GAMMA:** Gruppenantenne für militärische Mobilfunkaufklärung)

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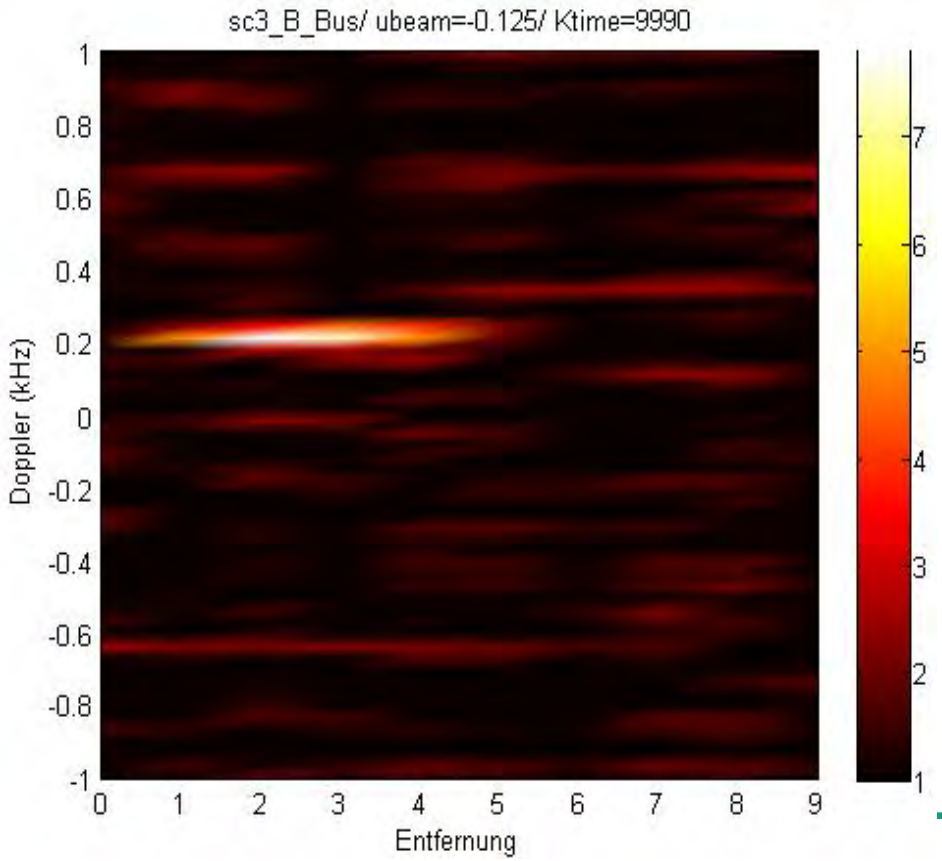
GSM Passive Radar: First Experiments (Oct. 2008)

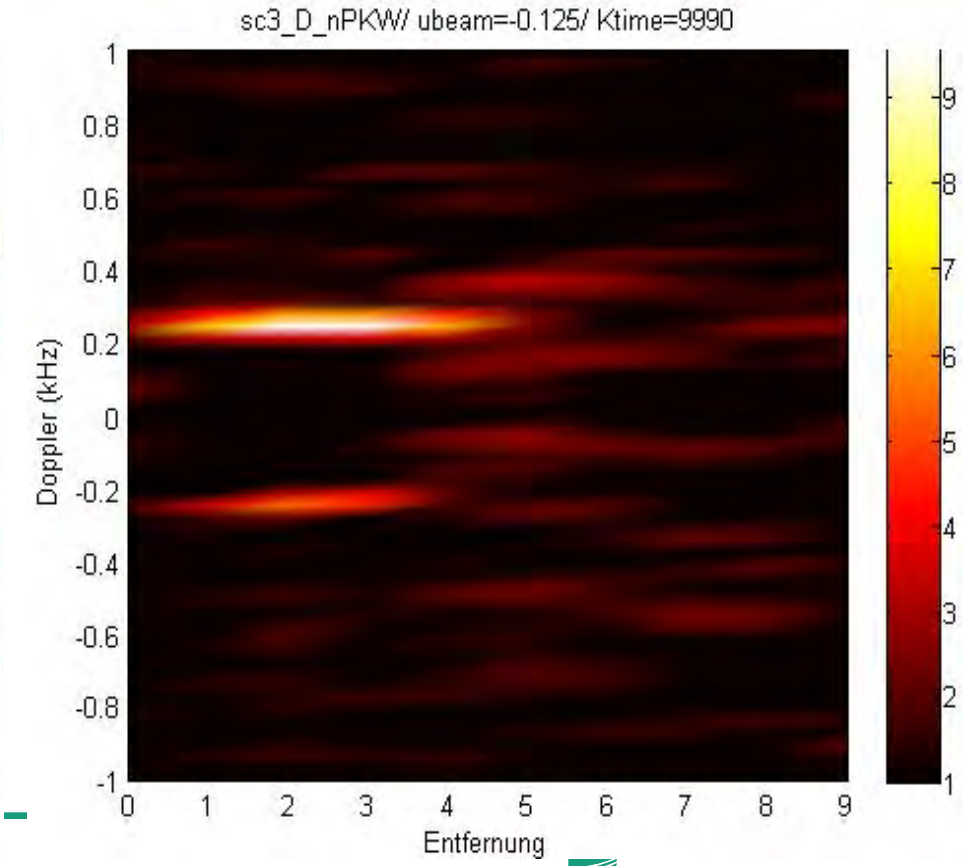
FGAN bus approaching with ca. 60km/h in 1.5 km distance

Corresponds to f_d= 200 Hz, range cell 3.2



Vehicles of opportunity: car convoy approaching (ca. 60km/h in 1.5km distance)

Simultaneously: car receding on other lane



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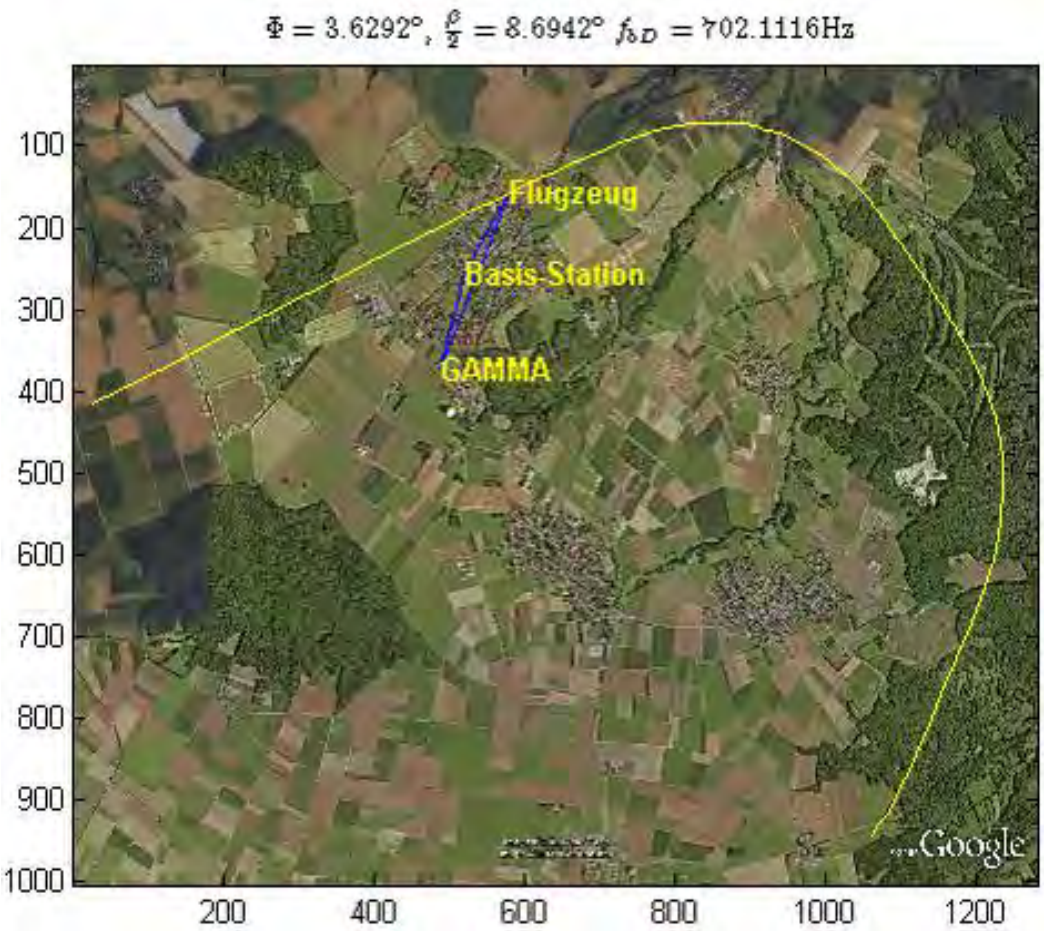
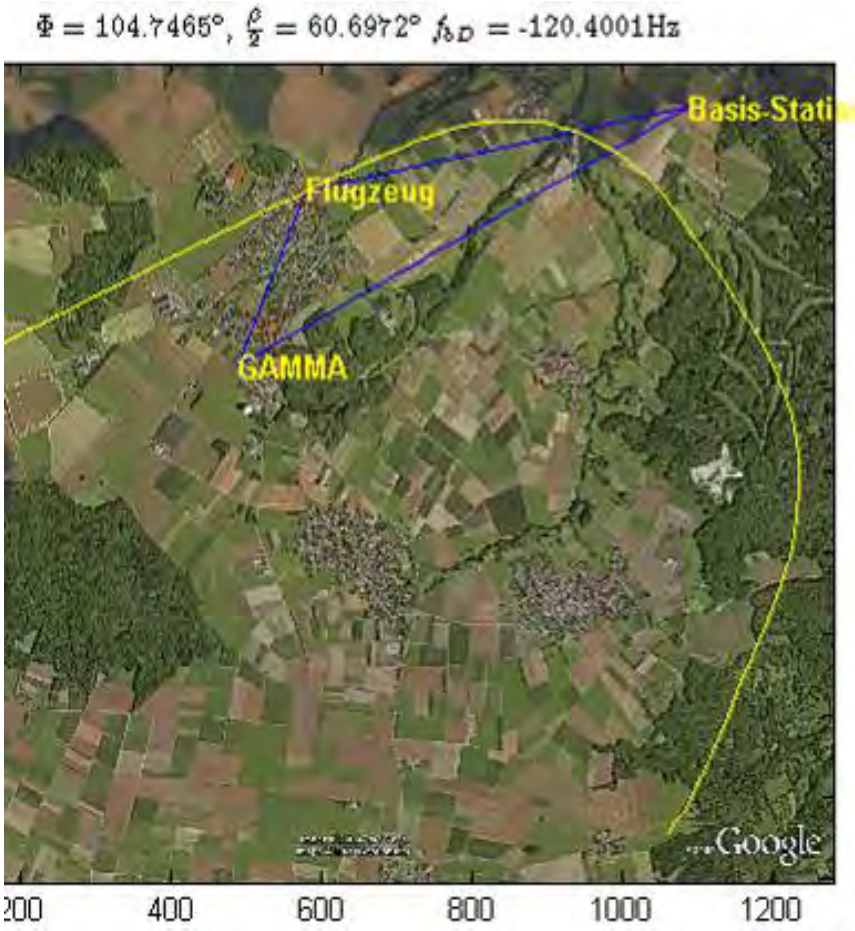
Measurements with TRANSALL Aircraft 23 June 2010





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Measurements with TRANSALL Aircraft 23 June 2009

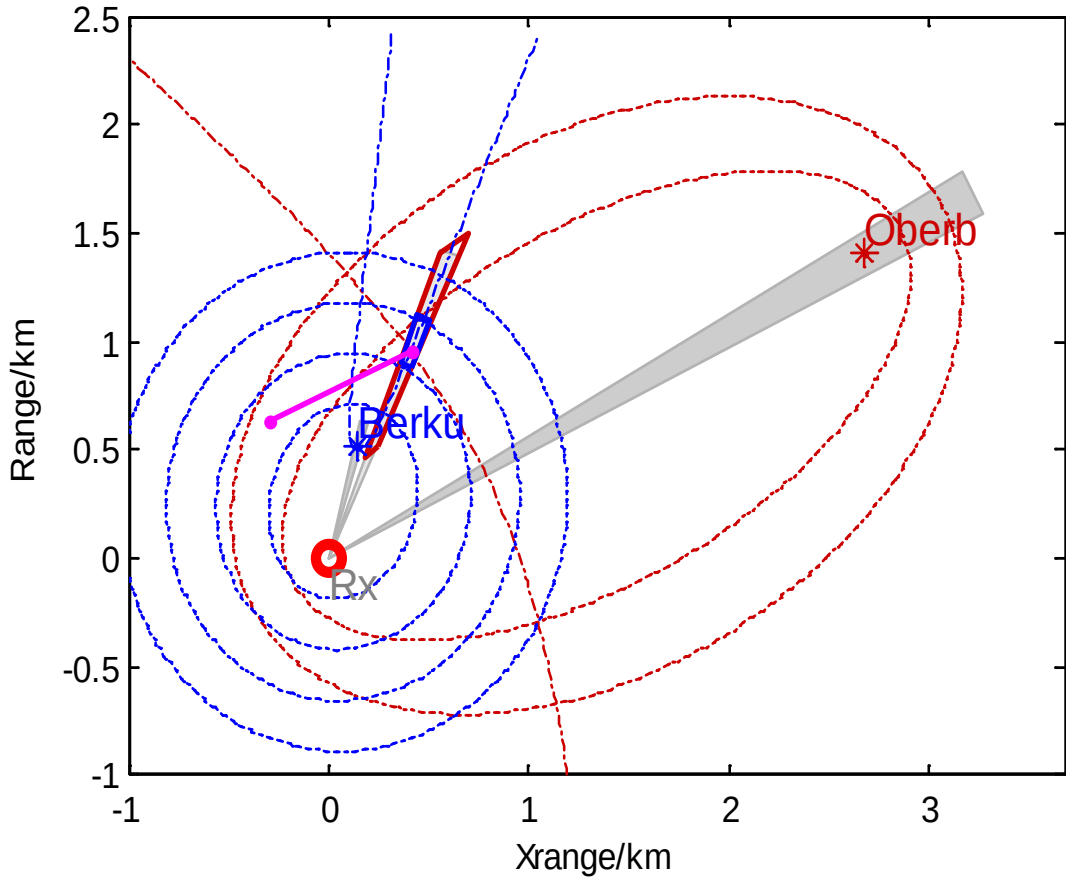
R.Oberb/km=3.0289
R.Berku/km=0.54478

Δr/km=0.466

r.Trans/km=1.069

Trans@bin 1 3

Trans@Dop -121 690



Base station Oberbachem
expected Doppler frequency -121 Hz
Range difference 380 m
◊Range bin 1

Base station Berkum
expected Doppler frequency 690 Hz
Range difference 1000 m
◊ Range bin 3

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Measurements with TRANSALL Aircraft 23 June 2009

R.Oberb/km=3.0289
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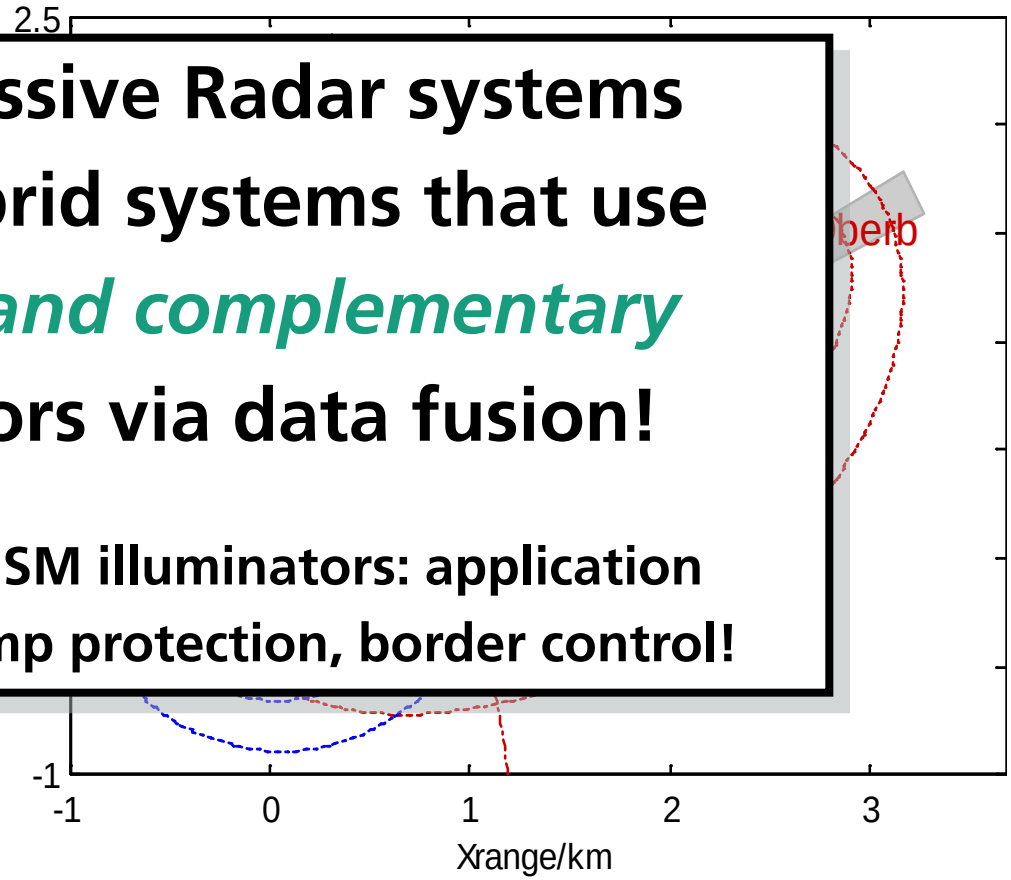

Robust Passive Radar systems will be hybrid systems that use *different and complementary* illuminators via data fusion!

Omnipresent GSM illuminators: application potential for camp protection, border control!

Base station
expected Do
Range differ
◊Range bin 1

Base station Berkum
expected Doppler frequency 690 Hz
Range difference 1000 m
◊ Range bin 3

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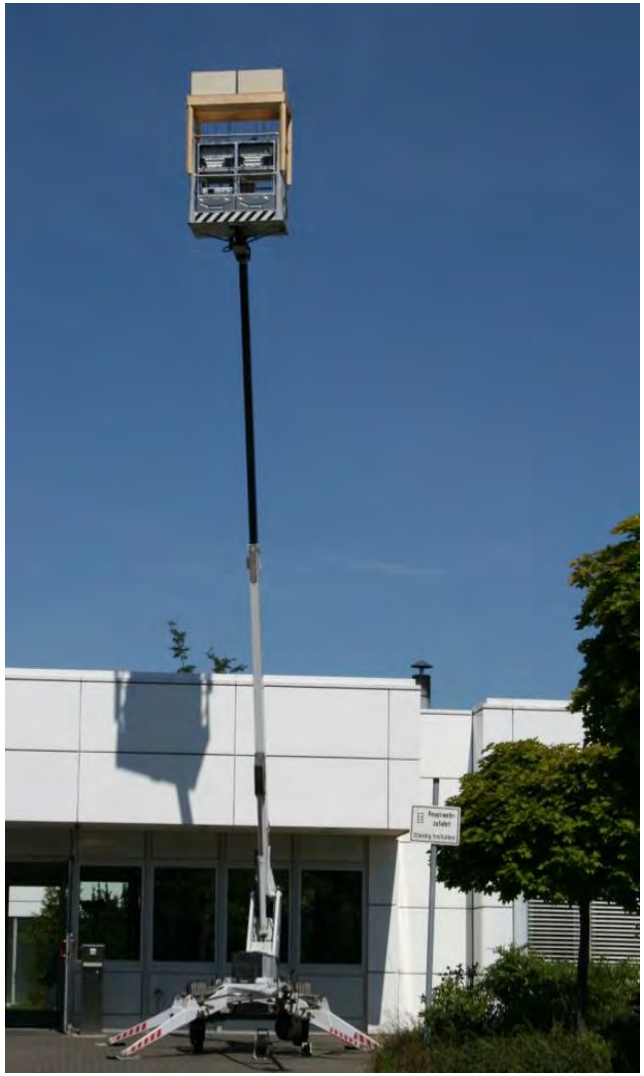
Mobiles Experimentalsystem GAMMA-2



Linear array with 16 elements

Separable into two blocks of 8 elements

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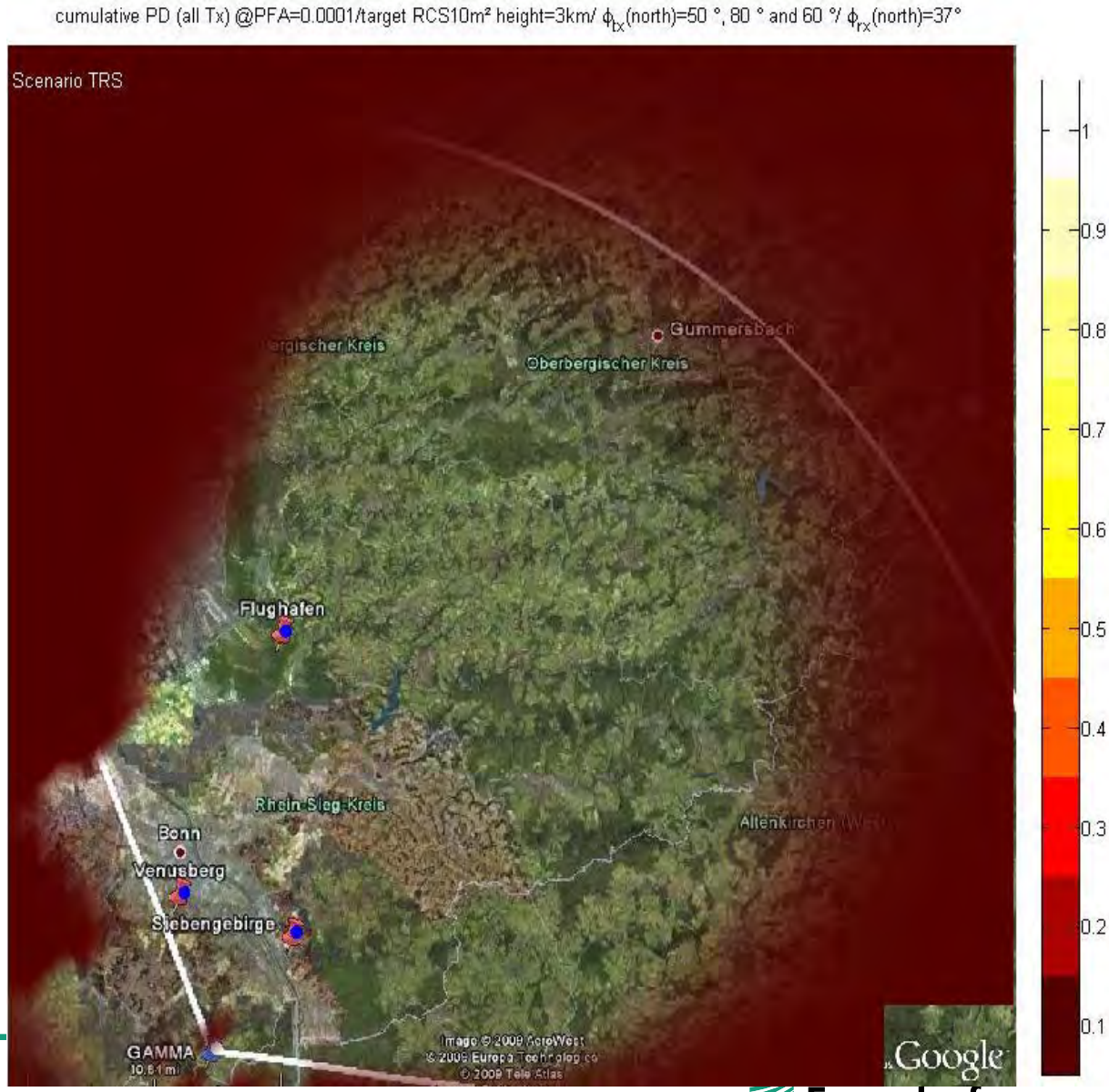
Coverage with GSM Radar by Fusing 3 Illuminators

Cumulative PD, PFA=10^{-4},
10m² target at 3km height



Dislocation of illuminators is decisive for illumination of the observation area!

→ GIS based base station selection manager is necessary – data base driven fusion task!

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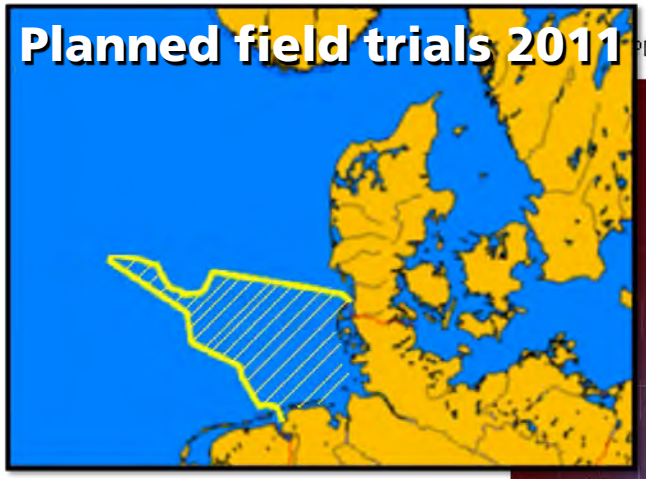
Expected passive detection range (ships)



Height of senders	60m
Middle target heigth	20m
PFA	10^{-3}
Integration time	3 s
RCS	10^3 m^2

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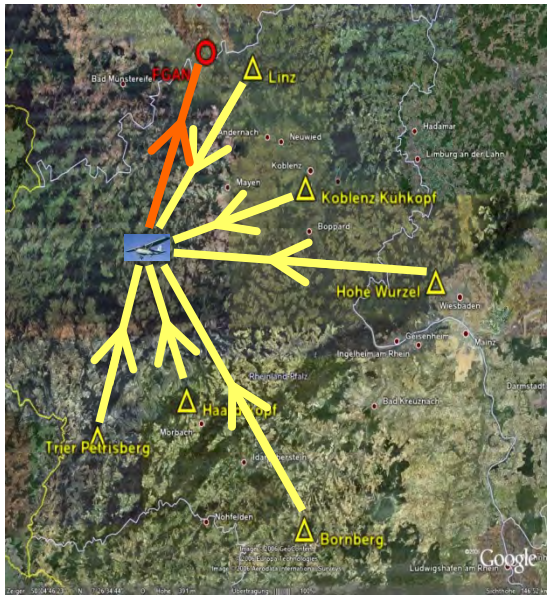
Multistatic Tracking: Non-cooperative Illumination

Topic: Passive Radar

SDF:
- DAB/DVB: single freq. networks
- Multiple stage MHT tracking
- De-ghosting algorithms
- Large, varying target numbers
- Joint demonstrator with FHR
- Experiments with EADS data
- PhD Thesis submitted 02/2010



Topic: Multistatic Sonar

SDF:
- Context: propagation models
- Cooperation with NURC, La Spezia
- Sea Campain “SeaBar 20ß8”
- `10: Multistatic UUV Experiments

NATO Undersea Research Centre
Partnering for Maritime Innovation

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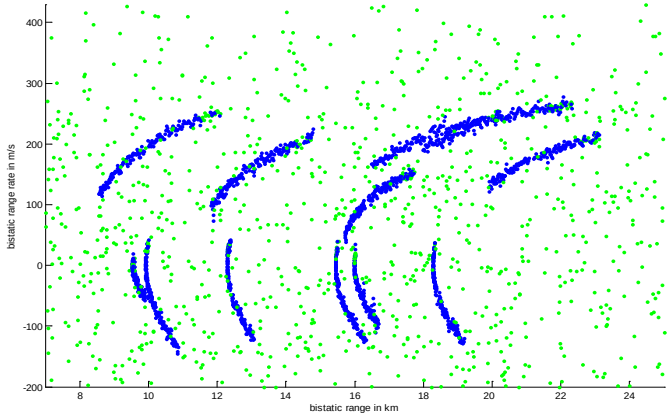
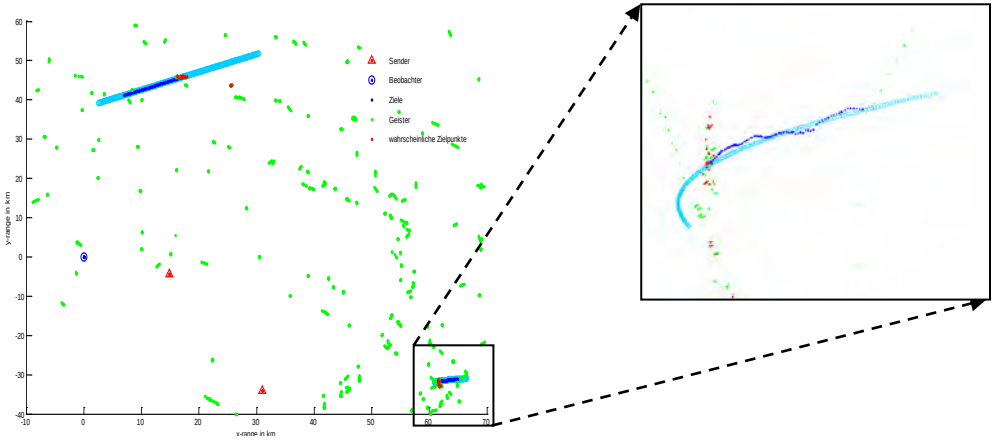
Multiple Stage Multihypothesis Tracking (overview)

Stage 1: Primary Tracking

Finds those measurements, that belong to a moving target

Two targets
Six illuminators



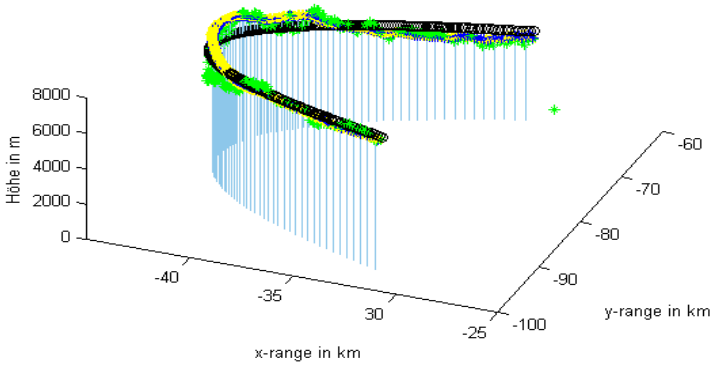


Stage 2: Deghosting in 2D

Evaluate association possibilities between target, measurement and illuminator

Stage 3: 3D-Tracking:

If association is known, measurements of more than two different illuminators can be used to do 3D-target tracking



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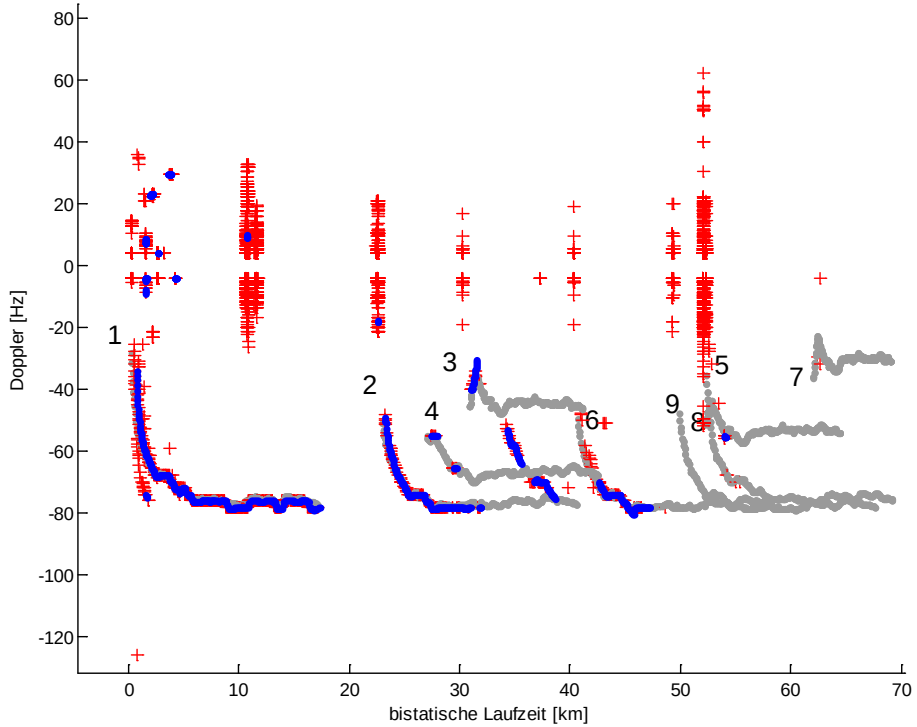
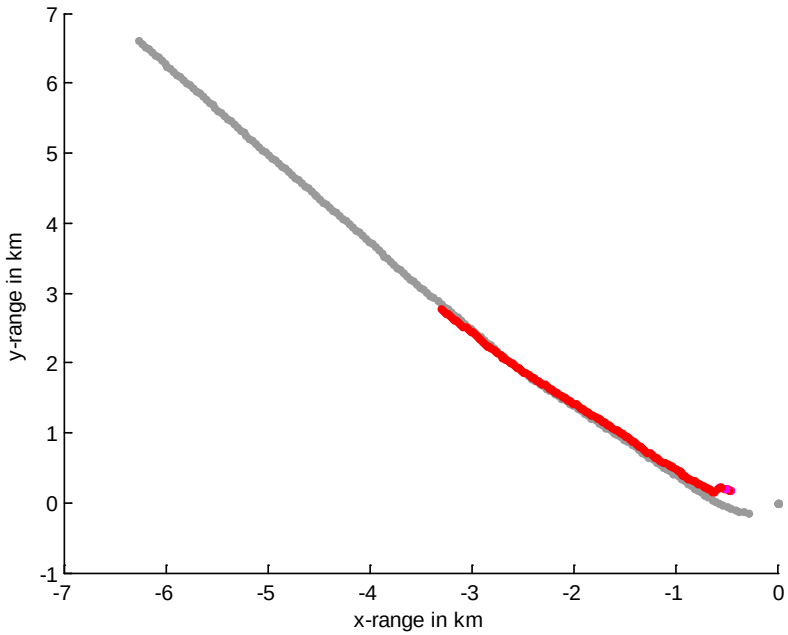
Tracking: Context Data on DAB/DVB-T Transmitter Positions





Range-Doppler-Plots (red: data, blue: tracks, grey: transformed ground truth)

End product: target track

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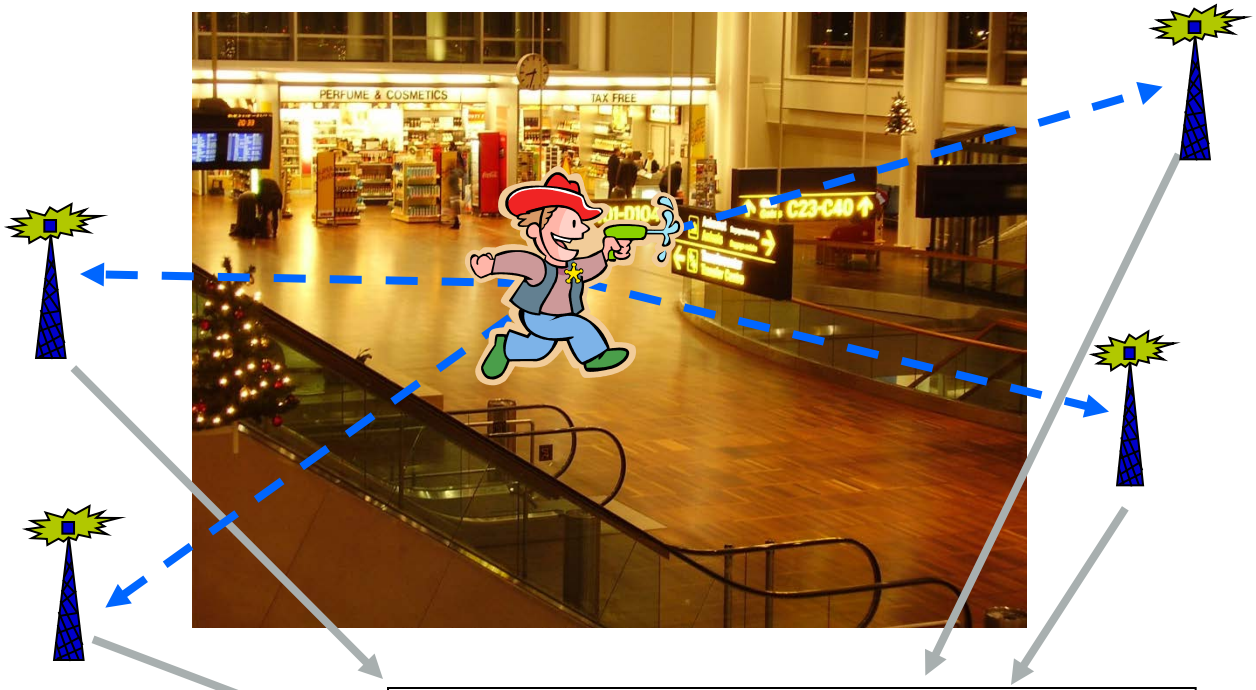
Task of the department SDF in ATOM:

Localization and Tracking of dangerous peoples based on passive multistatic sensors (for example WiFi)



Data fusion and advanced tracking

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